Department for Education

The impact of AI on UK jobs and training

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The impact of AI on UK jobs and training

Introduction

Advances in Artificial Intelligence (AI) are likely to have a profound and widespread effect on the UK economy and society, though the precise nature and speed of this effect is uncertain. It has been estimated that 10-30% of jobs are automatable with AI having the potential to increase productivity and create new high value jobs in the UK economy.[1,2] The UK education system and employers will need to adapt to ensure that individuals in the workforce have the skills they need to make the most of the potential benefits advances in AI will bring.

This report, produced by the Unit for Future Skills[3] in the Department for Education, is one of the first attempts to quantify the impact of AI on the UK job market (separate to automation more generally). The research takes a methodology from a US based study developed by Felten et al[4] and applies it for a UK context. The approach considers the abilities needed to perform different job roles, and the extent to which these can be aided by a selection of 10 common AI applications[5]. The methodology is extended further to consider which qualifications are more or less commonly held by workers in the AI-impacted jobs, using a novel dataset that links training routes to job occupation.

Results should be interpreted with caution

The estimates of which jobs are more exposed to AI are based on a number of uncertain assumptions so the results should be interpreted with caution. Quantifying occupations in terms of abilities to perform a job role will never fully describe all roles and a level of judgement is required when interpreting the results. Further, the extent to which occupations are exposed to AI will change due to the pace at which AI technologies are developing and as new data becomes available.

However, the themes highlighted by the analysis are expected to continue and provide a good basis for considering the relative impact of AI across different parts of the labour market.

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[1] PwC, Will robots really steal our jobs?

[2] The British Institute Academy, The impact of artificial intelligence on work

[3] https://www.gov.uk/government/groups/unit-for-future-skills

[4] Felten E, Raj M, Seamans R (2023) 'How will Language Modelers like ChatGPT Affect Occupations and Industries?'

[5] Abstract strategy games; real-time video games; image recognition; visual question answering; image generation; reading comprehension; language modelling; translation; speech recognition; instrumental track recognition.

Summary

This report shows the occupations, sectors and areas within the UK labour market that are expected to be most impacted by AI and large language models specifically. It also shows the qualifications and training routes that most commonly lead to these highly impacted jobs. The main findings are:

- **Professional occupations are more exposed to AI, particularly those associated with more clerical work and across finance, law and business management roles.** This includes management consultants and business analysts; accountants; and psychologists. Teaching occupations also show higher exposure to AI, where the application of large language models is particularly relevant.

- **The finance & insurance sector is more exposed to AI than any other sector.** The other sectors most exposed to AI are information & communication; professional, scientific & technical; property; public administration & defence; and education.

- **Workers in London and the South East have the highest exposure to AI,** reflecting the greater concentration of professional occupations in those areas. Workers in the North East are in jobs with the least exposure to AI across the UK. However, overall the variation in exposure to AI across the geographical areas is much smaller than the variation observed across occupations or industries.

- **Employees with more advanced qualifications are typically in jobs more exposed to AI.** For example, employees with a level 6 qualification (equivalent to a degree) are more likely to work in a job with higher exposure to AI than employees with a level 3 qualification (equivalent to A-Levels).

- **Employees with qualifications in accounting and finance through Further Education or apprenticeships, and economics and mathematics through Higher Education are typically in jobs more exposed to AI.** Employees with qualifications at level 3 or below in building and construction, manufacturing technologies, and transportation operations and maintenance are in jobs that are least exposed to AI.

The analysis measures the exposure of jobs to AI, rather than distinguishing whether a job will be augmented (aided) or replaced (substituted) by AI. Research by the International Labor Organization (ILO)[6] suggests that most jobs and industries are only partly exposed to automation and are more likely to be complemented rather than substituted by generative AI like ChatGPT. Annex 2 maps the jobs highlighted in that report to the UK job market, and generally include customer service and administrative occupations, including call and contact centre and unclassified administrative occupations.

[6] Generative AI and jobs: A global analysis of potential effects on job quantity and quality (ilo.org)

1 Methodology

The methodology broadly follows the approach described by Felten et al[7] to create an AI Occupational Exposure (AIOE) score, with some adaptations to make it suitable for a UK context.

1.1 Selection of AI applications

The AIOE is constructed based on assumptions around the use of a defined set of common AI applications. The 10 AI applications selected are based on those where the Electronic Frontier Foundation (EFF) has recorded scientific activity and progress in the technology from 2010 onwards.

Table 1: AI applications

AI application	Definition
Abstract strategy games	The ability to play abstract games involving sometimes complex strategy and reasoning ability, such as chess, go, or checkers, at a high level.
Real-time video games	The ability to play a variety of real-time video games of increasing complexity at a high level.
Image recognition	The determination of what objects are present in a still image.
Visual question answering	The recognition of events, relationships, and context from a still image.
Image generation	The creation of complex images.
Reading comprehension	The ability to answer simple reasoning questions based on an understanding of text.
Language modelling	The ability to model, predict, or mimic human language.
Translation	The translation of words or text from one language into another.
Speech recognition	The recognition of spoken language into text.
Instrumental track recognition	The recognition of instrumental musical tracks.

This set of applications does not comprehensively cover the set of applications for which AI could ultimately be used; however, based on further work conducted by Felten et al with field experts, it is believed that these represent fundamental applications of AI that

[7] Felten E, Raj M, Seamans R (2023) How will Language Modelers like ChatGPT Affect Occupations and Industries?

are likely to have implications for the workforce and are applications that cover the most likely and most common uses of AI.

1.2 Mapping human abilities to job roles

The methodology by Felten *et al* uses the Occupational Information Network (O*NET) database of occupational characteristics and worker requirements information across the US economy.[8] There is currently no equivalent database for UK occupations[9] so the O*NET data is mapped to the UK using a crosswalk between O*NET occupations and SOC 2010.

The O*NET system uses 52 distinct abilities to describe the workplace activities of each occupation, each with a separate score for ‘level’ and ‘importance’. Abilities are grouped under four categories: cognitive, physical, psychometer and sensory. Examples of abilities are oral comprehension, written expression, mathematical reasoning, manual dexterity, and stamina.[10]

SOC 2010 was used instead of SOC 2020 to align with information on training pathways and due to known issues with SOC 2020[11]. Updating the analysis to SOC 2020 will lead to small changes in the ordering of AIOE scores but not the overall findings.

1.3 Assessing AI applications against human abilities

AI applications are linked to workplace abilities using a crowd-sourced data set collected by Felten *et al*, and constructed using survey responses of “gig workers” from Amazon's Mechanical Turk (mTurk) web service. The data has a measure of application-ability relatedness for each combination bound between 0 and 1. This measure of application-ability relatedness is then organised into a matrix that connects the 10 AI applications to the 52 O*NET occupational abilities. An ability-level exposure is calculated as follows:

$$A_{ij} = \sum_{i=1}^{10} x_{ij} \qquad (1)'$$

In this equation, i indexes the AI application and j indexes the occupational ability. The ability-level exposure, A, is calculated as the sum of the 10 application-ability relatedness scores, x, as constructed using mTurk survey data. By calculating the ability-level AI

[8] Felten E, Raj M, Seamans R (2023) How will Language Modelers like ChatGPT Affect Occupations and Industries?

[9] https://www.gov.uk/government/publications/a-skills-classification-for-the-uk

[10] O*NET 28.0 Database at O*NET Resource Center (onetcenter.org)

[11] Revision of miscoded occupational data in the ONS Labour Force Survey, UK - Office for National Statistics

exposure as a sum of all the AI applications, all applications are weighted equally[12]. This approach assumes that each application has an independent effect on an ability and does not consider interactions across applications.

The estimates for each application are then standardised to give a rating between 0 and 1.

1.4 Calculating occupational exposure

For each occupation, the values for the level and importance of each ability are combined with the rating for the relatedness of each AI application to create an AI Occupational Exposure (AIOE) score. This is done overall for all AI applications, and individually for each application, e.g. language modelling.

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} \times L_{jk} \times I_{jk}}{\sum_{j=1}^{52} L_{jk} \times I_{jk}} \qquad (2)$$

In this equation, *i* indexes the AI application, *j* indexes the occupational ability, and *k* indexes the occupation. A_{ij} represents the ability-level exposure score calculated in Equation 1. The ability-level AI exposure is weighted by the ability's prevalence (L_{jk}) and importance (I_{jk}) within each occupation as measured by O*NET (mapped to SOC 2010) by multiplying the ability-level AI exposure by the prevalence and importance scores for that ability within each occupation, scaled so that they are equally weighted. These prevalence and importance scores, account for the presence of different abilities within an occupation. Abilities that are integral to an occupation have high prevalence and importance scores, while those that are used less often or are less vital have lower prevalence and importance scores. An occupation's aggregate exposure to AI is calculated by summing this weighted ability-level AI exposure across all abilities in an occupation. The scores are then standardised and ranked from most to least exposed. These scores are applied to employment counts across occupations to give aggregate exposure scores, for example across the geographical areas.

In testing the robustness of their methodology Felten *et al* found evidence that AI is most likely to affect cognitive and sensory abilities, and the AIOE scores were not sensitive to excluding any of the applications in the sample. Therefore, any AI applications that may have been excluded are also likely to be related to a similar set of cognitive and sensory abilities.

[12] Felten et al carried out further analysis which suggested that weighting the applications is unlikely to have a meaningful impact on the measure.

1.5 Mapping occupations to training pathways

Relationships between occupations and training are taken from ASHE-LEO data, a new data resource available in the Department for Education. It brings together the longitudinal education and labour market information in the Longitudinal Education Outcomes study (LEO)[13] with the information on employment and earnings in the Annual Survey of Hours and Earnings (ASHE).[14]

There are around 100,000 individuals in the ASHE-LEO sample in each year. This represents 45-75% of the overall ASHE sample, with later years having a better match rate than earlier years, and younger ages having a better match rate than older ages. ASHE-LEO is used here as an approximately representative sample of early career employees in LEO (employees aged 23-30 in the 2018-19 tax year).

The data is used to identify the training taken by employees for each occupation. As each training route may be associated with multiple occupations, a weighted average is calculated to arrive at an average AIOE score.

1.6 Data sources

Name	Description
AIOE data[15]	Organised measure of application-ability relatedness that connects the 10 EFF AI applications to the 52 O*NET occupational abilities.
Annual Population Survey	A residence based labour market survey encompassing population, economic activity (employment and unemployment), economic inactivity and qualifications.
Apprenticeship data	Apprenticeships starts in England reported for an academic year based on data returned by providers.
ASHE-LEO	Education and labour market information in the Longitudinal Education Outcomes study (LEO) linked with the information on employment and earnings in the Annual Survey of Hours and Earnings (ASHE)

[13] Apply to access the Longitudinal Education Outcomes (LEO) dataset - GOV.UK (www.gov.uk)

[14] Annual Survey of Hours and Earnings (ASHE) - Office for National Statistics (ons.gov.uk)

[15] Felten E, Raj M, Seamans R (2021) Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. Strategic Management Journal 42(12):2195–2217

1.7 Research by International Monetary Fund

The International Monetary Fund (IMF) have constructed a complementarity adjusted AI occupational exposure (C-AIOE) measure, where the exposure of occupations to AI are mitigated by their potential for complementarity.[16]

At a high level the authors of this study make an adjustment to the Felten *et al* methodology for AIOE[17] to capture the potential to complement or substitute for labour in each occupation. They then apply both the original measure and the complementarity adjusted measures to labour force microdata (using ISCO-08) from 6 countries including the UK, with a particular focus on emerging markets.

The research finds that there are substantial cross-country disparities in the baseline AIOE, with emerging markets generally displaying lower exposure levels than advanced economies. This disparity is mainly due to different employment structures, with advanced economies characterised by larger proportions of high-skill occupations such as professionals and managers. In line with this report and as outlined by Felten *et al*, these professions are the most exposed to AI due to their high concentration of cognitive-based tasks. However, because those high-skill occupations also show higher potential for AI complementarity, these cross-country disparities in terms of potentially disruptive exposure reduce considerably once complementarity is factored in. Nevertheless, advanced economies remain more exposed even under the C-AIOE measure. Emerging markets with a large share of agricultural employment, remain relatively less exposed under both measures, as occupations in this sector have very low baseline exposure to AI. Overall, the results suggest that the impact of AI on labour markets in advanced economies may be more "polarised," as their employment structure better positions them to benefit from growth opportunities but also makes them more vulnerable to likely job displacements.

[16] Labor Market Exposure to AI: Cross-country Differences and Distributional Implications (imf.org)

[17] Felten E, Raj M, Seamans R (2023) 'How will Language Modelers like ChatGPT Affect Occupations and Industries?'

2 Occupational exposure to AI

This report estimates the relative expose of UK jobs to AI as opposed to the absolute impact of AI. It attempts to identify which jobs will be more affected than others, how much overall jobs or the UK labour market may change. There is a range of UK and international research on AI and the absolute impact that it will have on jobs and the labour market[18]

This analysis assesses the relative exposure of UK jobs[19] to AI by use of an **AI Occupational Exposure (AIOE) score**. The AIOE score allows jobs to be ranked to show which jobs are more and less likely to be impacted by advances in AI, based on the abilities required to perform the job. As well as AI generally, a similar exposure score is created to consider large language modelling specifically through generative AI tools like ChatGPT and Bard.

The analysis measures the exposure of jobs to AI, rather than distinguishing whether a job will be augmented (aided) or replaced (substituted) by AI. Annex 2 discusses the potential for identifying UK jobs which could be fully automated as a result of AI based on research from the International Labor Organization (ILO).

2.1 Occupations most exposed to AI

Table 2 shows a list of the top 20 occupations that are most exposed to AI, and to large language modelling specifically. A full list of all occupations is published alongside this report.

The exposure score is based on several assumptions including the abilities considered important for a job at a given point in time so **rankings should be interpreted with caution**, however the themes highlighted by the analysis are expected to continue[20].

The occupations most exposed to AI include more professional occupations, particularly those associated with more clerical work and across finance, law and business management roles. This includes management consultants and business analysts, accountants, and psychologists. This compares to the occupations least exposed to AI, which include sport professionals, roofers and steel erectors.

[18] It is very difficult to make a numerical estimate on a technology which is not yet fully understood and is evolving at a rapid pace. A consensus has begun to emerge that 10-30% of jobs in the UK are highly automatable and could be subject to some level of automation over the next two decades. However, the overall net effect on employment is unclear but it is often assumed that there will be a broadly neutral long-term effect and job displacement will be matched by job creation. (See, for instance, Will robots really steal our jobs? (pwc.co.uk))

[19] Defined by 4 digit standardised occupation classification (SOC 2010) codes.

[20] Felten et al (2021) Appendix C: Quantitative Validation of the AIOE and Related Measures

The list of occupations most exposed to large language modelling includes many of the same occupations exposed to AI more generally, with both lists including solicitors, psychologists and management consultants and business analysts. It also includes more education related occupations, particularly for post-16 training. This aligns with public statements around the potential use of generative AI tools by teachers, for example in preparing teaching material.[21]

Table 2: Occupations most exposed to AI and large language modelling

	Exposure to all AI applications	**Exposure to large language modelling**
1	Management consultants and business analysts*	Telephone salespersons
2	Financial managers and directors	Solicitors*
3	Charted and certified accountants	Psychologists*
4	Psychologists*	Further education teaching professionals
5	Purchasing managers and directors	Market and street traders and assistants
6	Actuaries, economists and statisticians	Legal professionals n.e.c.*
7	Business and financial project management professionals	Credit controllers*
8	Finance and investment analysts and advisers	Human resource administration occupations*
9	Legal professionals n.e.c.*	Public relations professionals
10	Business and related associate professionals n.e.c.	Management consultant and business analysts*
11	Credit controllers*	Market research interviewers
12	Solicitors*	Local government administrative occupations
13	Civil engineers	Clergy
14	Education advisers and school inspectors*	Higher education teaching professionals
15	Human resources administrative occupations*	Collector salespersons and credit agents
16	Business, research and administrative professionals n.e.c.	Education advisers and school inspectors*
17	Financial accounts managers	Human resource managers and directors
18	Bookkeepers, payroll managers and wages clerks	National government administrative occupations*
19	National government administrative occupations*	Vocational and industrial trainers and instructors
20	Marketing associate professionals	Social and humanities scientists

* Occupations that appear in both lists are marked with an asterisk.

[21] 'Call for evidence on generative artificial intelligence in education' Department for Education 2023

Table 3 shows a list of the occupations that are least exposed to AI, and to large language modelling specifically.

The occupations least exposed to AI and LLM include many of the same areas, including more manual work that is technically difficult, in unpredictable environments, and with lower wages (reducing the incentive to automate) – with the exception of sports players. This includes: roofers, roof tilers and slaters; elementary construction occupations; plasterers; and steel erectors.

Table 3: Occupations least exposed to AI and large language modelling

	Exposure to all AI applications	Exposure to large language modelling
1	Sports players*	Fork-lift truck drivers*
2	Roofers, roof tilers and slaters*	Roofers, roof tilers and slaters*
3	Elementary construction occupations*	Steel erectors*
4	Plasterers*	Vehicle valeters and cleaners*
5	Steel erectors*	Elementary construction occupations*
6	Vehicle valeters and cleaners*	Plasterers*
7	Hospital porters	Metal plate workers, and riveters*
8	Cleaners and domestics	Vehicle paint technicians
9	Floorers and wall tilers*	Floorers and wall tilers*
10	Metal plate workers, and riveters	Mobile machine drivers and operatives n.e.c.
11	Launderers, dry cleaners and pressers*	Launderers, dry cleaners and pressers*
12	Window cleaners	Large goods vehicle drivers
13	Painters and decorators	Road construction operatives*
14	Fork-lift truck drivers*	Rail construction and maintenance operatives
15	Packers, bottlers, canners and fillers	Industrial cleaning process occupations
16	Gardeners and landscape gardeners	Elementary process plant occupations n.e.c.
17	Bricklayers and masons*	Sewing machinists
18	Road construction operatives*	Sports players*
19	Elementary process plant occupations n.e.c.*	Street cleaners
20	Tyre, exhaust and windscreen fitters	Bricklayers and masons*

* Occupations that appear in both lists are marked with an asterisk.

The rest of this report focusses on the impact of AI. The findings for large language models specifically are very similar to the findings for AI and are discussed further in Annex 4.

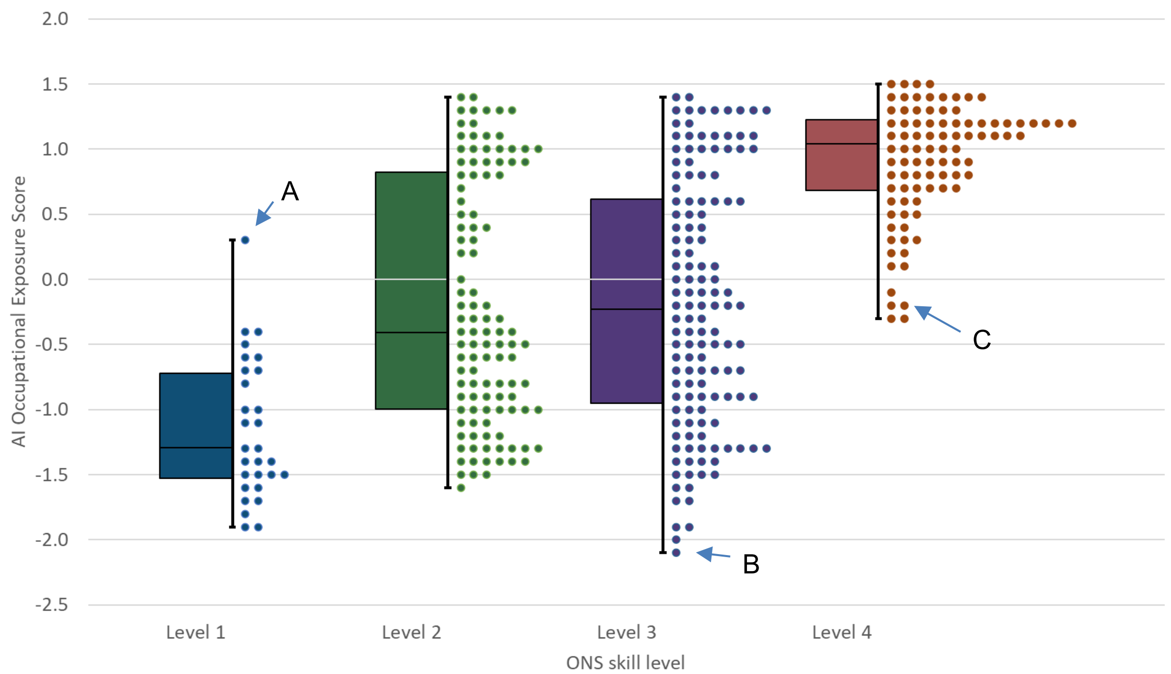
2.2 Exposure to AI by skill level of occupation

The ONS assign each occupation to one of four skill levels[22] gained through education or work-related experience:

- Level 1 – general compulsory education.
- Level 2 – general compulsory education with a longer period of work-related training or work experience.
- Level 3 – post-compulsory education below degree level.
- Level 4 – professional occupations normally requiring a degree or equivalent period of relevant work experience.

Figure 1 shows that professional occupations (those at skill level 4) are more exposed to AI than other occupations. These include many of the top 20 occupations listed in the previous section, including management consultants and business analysts, financial managers and directors, chartered and certified accountants, and psychologists.

Figure 1: Exposure to all AI by skill level of occupation



How to read this chart

- The boxes show the upper 25%, lower 25%, and average value for the AIOE score.
- The error bars show the highest and lowest AIOE scores.
- Each dot represents the AIOE score of an individual occupation.
- The AIOE score is a relative measure so negative values still indicate some exposure to AI.

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[22] SOC2010 volume 1: structure and descriptions of unit groups - Office for National Statistics

The professional occupations least exposed to AI (marked by ‘C’ on Figure 1) are veterinarians, medical radiographers, dental practitioners, physiotherapists, and senior police officers. Despite being less exposed to AI compared to other professional occupations, they rank among the middle for exposure to AI across all occupations. It may be expected that occupations such as radiographers would be more exposed, but this may be explained by the current use of technology and AI within these roles.

Similarly, those occupations requiring the lowest levels of education or relevant work experience are less exposed to AI (those at skill level 1). The exception to this is security guards (as shown by ‘A’ in Figure 1) where potential uses of AI have been documented to be anything from monitoring live video to AI powered patrol bots.[23] Whilst lower skilled occupations are generally less exposed to AI, there are still some higher skilled occupations at skill level 3 that are less exposed, such as roofers and sports players (as shown by ‘B’ in Figure 1).

These results are consistent with the findings of similar research[24] which suggests that occupations requiring a lower level of education tend to be more manual and often technically difficult roles, which have already seen extensive changes due to developments in technologies, and it is unlikely to be cost effective to apply further automation.[25, 26] Furthermore, more recent advancements in AI have been more applicable to software and technologies and either require skills in technical coding or use of specific software as part of the job, e.g. accountancy and finance.

[23] Artificial Intelligence and its applications in physical security | G4S United Kingdom

[24] Eloundou et al (2023), Felten et al (2023), Brynjolfsson et al (2023)

[25] How automation has affected jobs through the ages | World Economic Forum (weforum.org)

[26] AI-and-work-evidence-synthesis.pdf (thebritishacademy.ac.uk)

3 Exposure to AI across industries and geography

3.1 Exposure to AI across industry

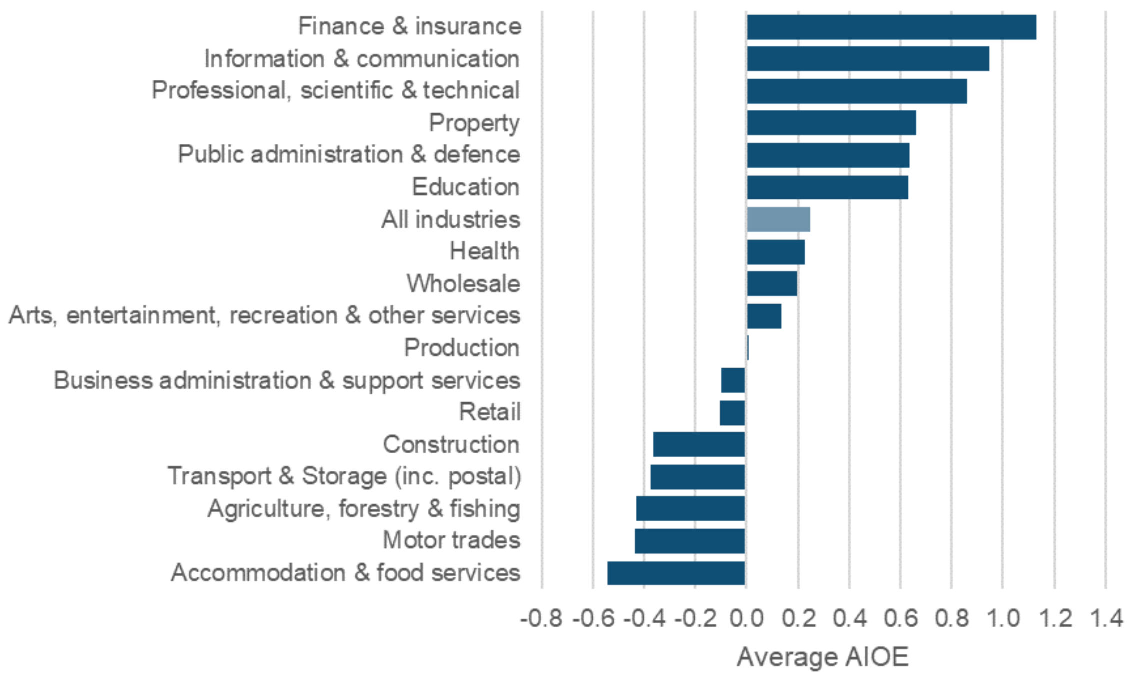
The industry estimate of exposure to AI is constructed by taking a weighted average of the AI Occupational Exposure (AIOE) scores across occupations within an industry. This provides an average AIOE score for each industry, which are shown in Figure 2. In general, the industries more exposed to AI follow the same themes as discussed earlier in this report.

The finance & insurance sector is more exposed to AI than any other sector. This sector features a large number of finance and clerical roles which have high AIOE scores. There are five other sectors that are highly exposed to AI: information & communication; professional, scientific & technical; property; public administration & defence; and education.

The industries least exposed to AI are accommodation & food services; motor trades, agriculture, forestry, and fishing; transport & storage and construction.

Some of these industries capture a range of activities. For example, the veterinary activities sub-sector has much lower exposure to AI (average AIOE of -0.06) compared to the professional, scientific & technical industry as whole (average AIOE of 0.86).

Figure 2: Exposure to AI by industry



3.2 Exposure to AI by geography

The geographical estimate of exposure to AI is constructed by taking a weighted average of the AI Occupational Exposure (AIOE) scores across occupations within a geographical area. This provides an average AIOE score for each geographical area or nation of the UK, which are shown in Figure 3.

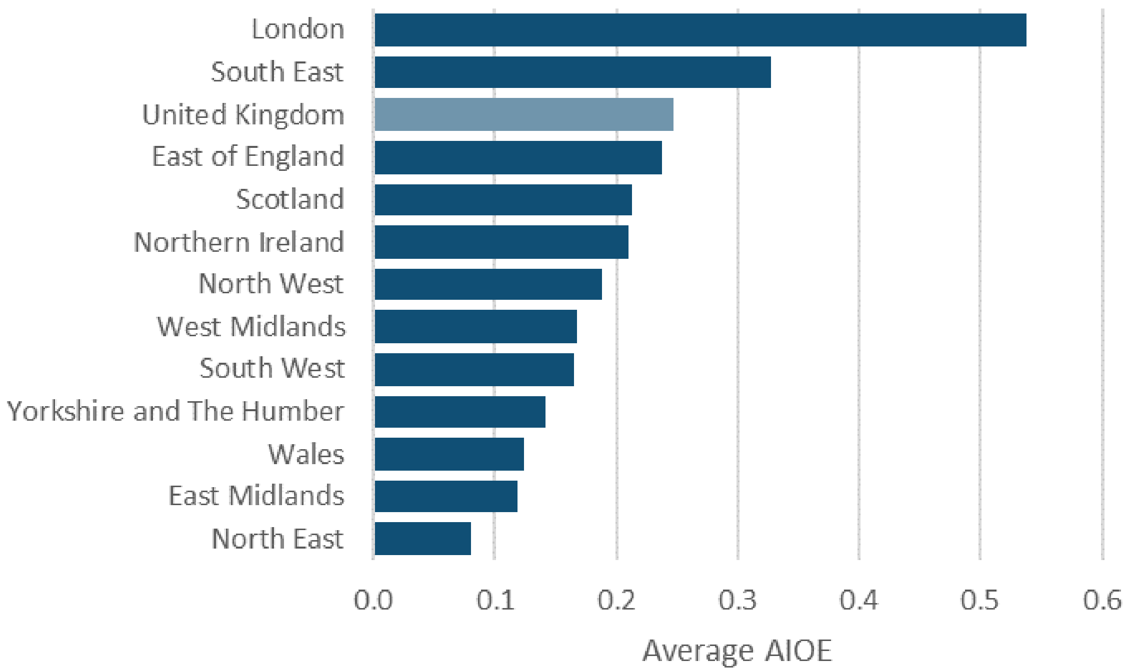
Overall, workers in London and the South East have the highest exposure to AI across any geographical area of the UK. They are also the only areas to be above the average for the UK as a whole. The North East is the area with the least exposure to AI across the UK.

Comparing London to the North East, the increased exposure is due to London having:

- A higher proportion of professional occupations, including programmers, financial managers, and IT professionals.
- A lower proportion of elementary trades, administration and services occupations, skilled trades, and caring personal services occupations.

Overall, the variation in exposure to AI across the geographical areas is much smaller than the variation across occupations or industries. Each geographical area covers a large population and a lot of overlap in the types of jobs, so we would expect to see more variation in exposure to AI when looking at smaller areas where the job markets will differ more[27].

Figure 3: Exposure to AI by geography



[27] At 4 digit SOC, between 55% and 80% of occupations within an individual geographical area or nation match the proportions seen for the UK as a whole.

4 Exposure to AI by qualification

An average AI occupational exposure score by highest qualification is estimated by linking together information on training with jobs. This is done using sample data that covers the qualifications held and training routes taken for young people in employment (age 23-30).[28]

4.1 Training routes

Figure 4 shows that early-career employees with higher levels of qualification are typically in occupations more exposed to AI. This aligns with findings from earlier in this report showing occupations labelled as higher skills levels were more exposed to AI. The same pattern is seen overall and across different training routes, for example apprenticeships, as shown in Figure 5. Female students are also in training that leads to more exposure to AI in jobs (overall their exposure score is 0.34 compared to 0.06 for males).

Employees that achieved apprenticeships at level 4 and above are in jobs most exposed to AI compared to any other route. However, this is based on a small sample, and the reference period for the data means it mainly includes the level 4 and 5 apprenticeship frameworks available before the introduction of new standards and growth in higher level apprenticeships from 2017 onwards. These apprenticeships were predominantly in accounting, professional services and IT, which typically are held by those in the occupations that are most exposed to AI.

In Annex 1, similar estimates have been made on the average exposure to AI using apprenticeship occupational maps and more recent data on apprenticeship starts. These estimates suggest employees with a level 4 or 5 qualification achieved through an apprenticeship are linked to jobs more exposed to AI than those that achieved similar level qualifications in Further Education or Higher Education settings.

[28] Longitudinal Education Outcomes study (LEO) linked to the Annual Survey of Hours and Earnings (ASHE).

Figure 4: Exposure to AI by highest level of attainment for early-career employees

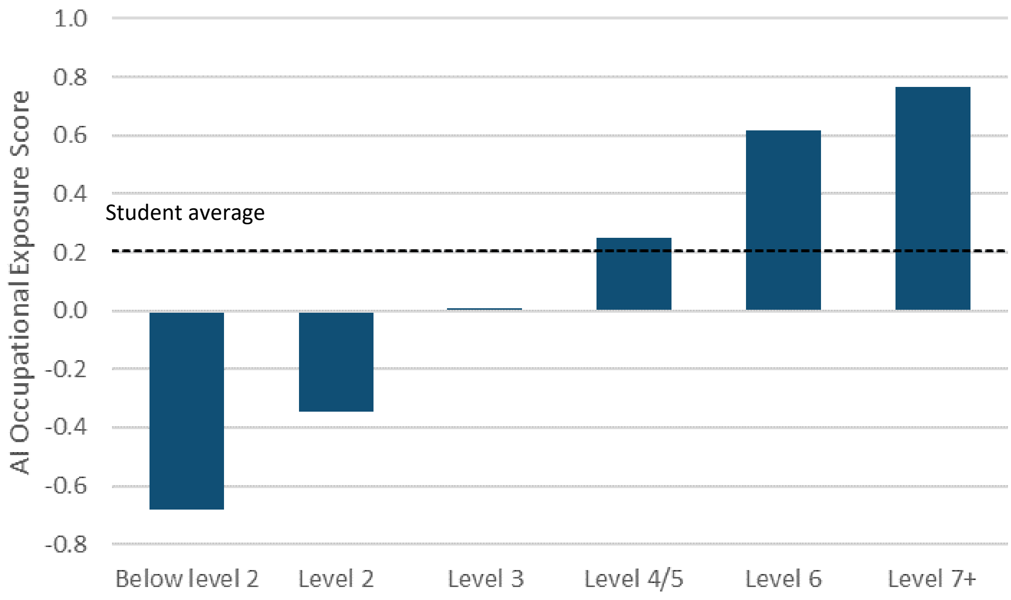
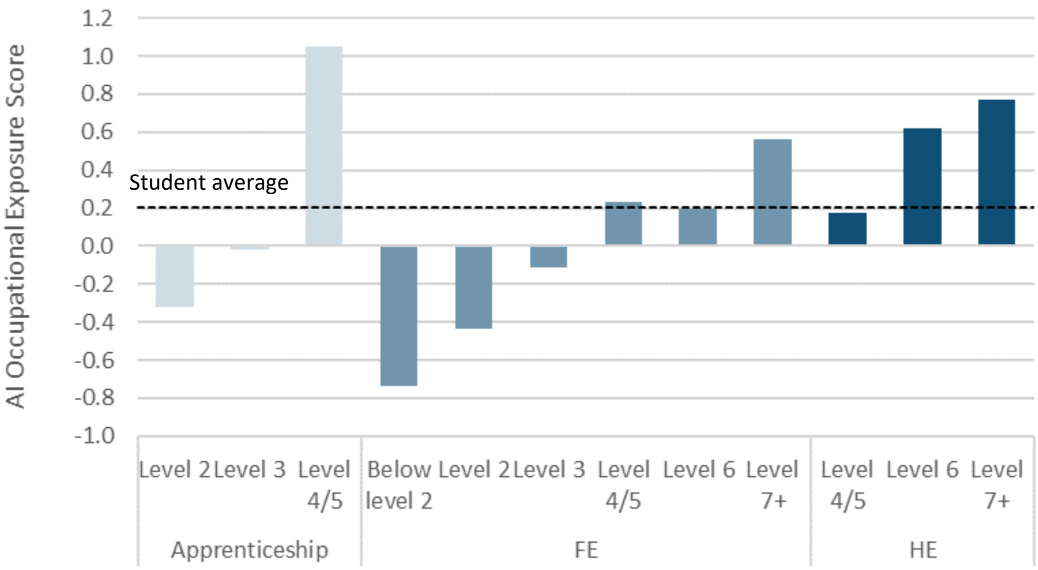


Figure 5: Exposure to AI by training route[29] for early-career employees



4.2 Subject areas

The tables below show more detail on the subject area for the highest qualification held by employees and show similar findings to earlier in the report around occupations and sectors most impacted by AI.

Early-career employees that achieved qualifications in accounting and finance at level 4 and above are in jobs more exposed to AI than any other subject area across Further

[29] Higher Education and Further Education refers to the education setting.

Education or apprenticeships. Employees that achieved a level 7 or higher qualification in economics or mathematics and statistics are in jobs most exposed to AI across all subjects in Higher Education. This reflects a high number of learners with these qualifications ending up in professional occupations, including in the finance and insurance sector.

The employees with the lowest exposure to AI are those that achieved level 2 or 3 qualifications in building and construction, manufacturing technologies, and transportation operations and maintenance.

Table 4: Subjects most and least associated with exposure to AI by further education setting

	Level	Subject	AIOE
Top 5	Level 4/5	Accounting and finance	1.22
	Level 4/5	Building and construction	0.51
	Level 3	Administration	0.46
	Level 3	Business management	0.26
	Level 6	Crafts, creative arts and design	0.21
Bottom 5	Level 3	Transportation operations and maintenance	-0.65
	Below level 2	Foundations for learning and life	-0.66
	Level 2	Building and construction	-0.74
	Level 2	Manufacturing technologies	-0.78
	Level 2	Preparation for work	-0.79

Table 5: Top 5 subjects most and least associated with exposure to AI by apprenticeship setting

	Level	Subject	AIOE
Top 5	Level 4/5	Accounting and finance	1.31
	Level 3	Accounting and finance	1.10
	Level 3	Administration	0.75
	Level 3	Marketing and sales	0.53
	Level 3	ICT practitioners	0.52
Bottom 5	Level 2	Manufacturing technologies	-0.66
	Level 3	Transportation operations and maintenance	-0.73
	Level 2	Transportation operations and maintenance	-0.74
	Level 3	Building and construction	-0.80
	Level 2	Building and construction	-0.92

Table 6: Top 5 subjects most and least associated with exposure to AI by higher education setting[30]

	Level	Subject	AIOE

[30] Higher Education training has been mapped to the sector subject area classification for Further Education.

Top 5	Level 7+	Economics	1.26
	Level 7+	Mathematics and statistics	1.15
	Level 6	Economics	1.14
	Level 6	Accounting and finance	1.07
	Level 7+	Law and legal services	1.04
Bottom 5	Level 4/5	Sport, leisure and recreation	0.11
	Level 4/5	Leisure, Travel and Tourism	0.10
	Level 4/5	Engineering	0.08
	Level 4/5	Sociology and social policy	0.05
	Level 6	Animal care and veterinary science	-0.03

1. The AI occupational exposure scores relate to the job that the individual was employed in which may not be directly associated with their training.
2. Not all subject areas are included due to low sample sizes.
3. Higher Education and Further Education refers to the education setting.
4. Higher Education training has been mapped to the sector subject area classification for Further Education.

Annex 1: Apprenticeships

All apprenticeships are based on occupations recognised by employers. The Institute for Apprenticeships and Technical Education (IfATE) have developed occupational maps that bring these together to show where apprenticeships can lead.[31] These occupational maps can be used together with data on apprenticeship participation to show the apprenticeships that lead to jobs with the most exposure to AI.[32]

Unlike the analysis in the main body of the report these maps do not show the full range of occupations that people may actually take up after completing a standard but do provide a good relationship to the skills that would be expected in those occupations.

Figure 6: Expected exposure to AI by apprenticeship level (using occupational maps)

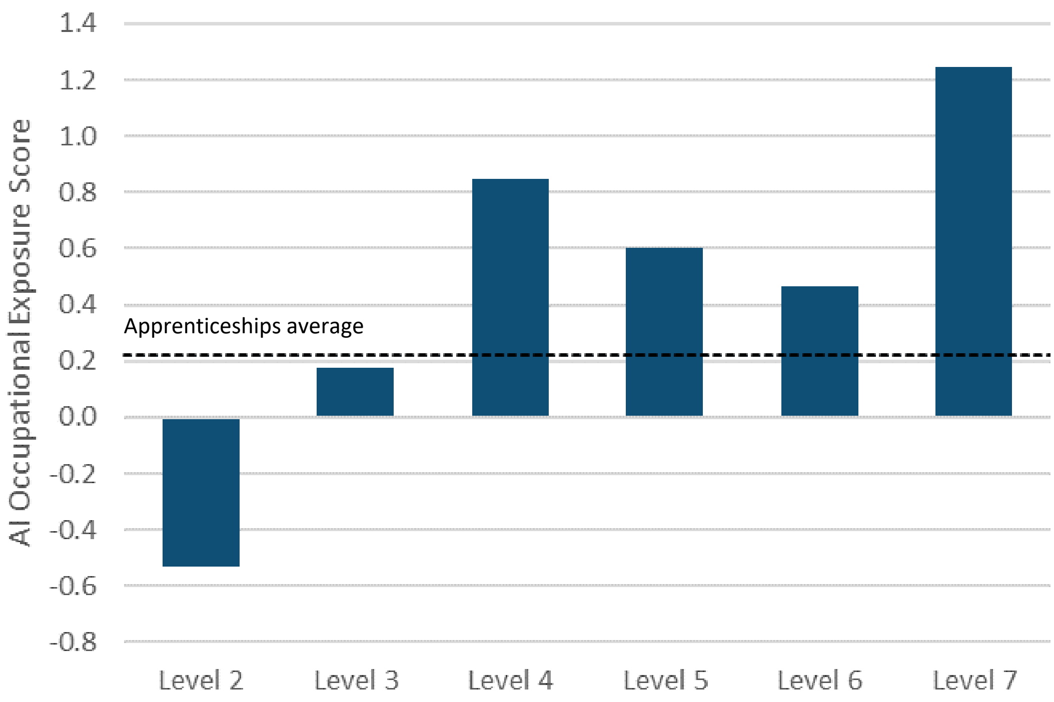


Figure 6 shows that higher level apprenticeships are expected to lead to jobs with the most exposure to AI. This is consistent with the findings in the main report. Level 4 and level 5 apprenticeships are expected to lead to occupations with higher exposure to AI than level 6 apprenticeships, though this may be due to a small number of popular standards overly impacting on the average. The level 6 standards 'Police Constable' and 'Registered Nurse Degree' alone account for nearly 30% of starts at level 6 and have relatively low AIOE scores. Excluding these two standards would increase the level 6 average AIOE to 0.81, far closer to the level 4 exposure score.

[31] Occupational maps / Institute for Apprenticeships and Technical Education

[32] IfATE occupational maps are mapped from SOC 2020 to SOC 2010 to align with the classification of the exposure data. The methodology covers 99.2% of apprenticeship starts in the data for 2022/23 Q3.

The top 5 apprenticeships standards leading to jobs most exposed to AI (and with more than 1,000 starts) are:

1. Level 4 Business Analyst
2. Level 7 Accountancy or Taxation Specialist
3. Level 4 Associate Project Manager
4. Level 3 Data Technician
5. Level 3 Assistant Accountant

Annex 2: Augmentation versus substitution

Research from the International Labor Organisation (ILO)[33] used statistical methods to categorise the impact of AI on occupations as either 'high augmentation' or 'high automation' (or 'high substitution'). The analysis is not UK specific and uses a different methodology including an international occupational classification system (ISCO) to categorise occupations. This has been mapped across to UK occupations using a crosswalk between ISCO and SOC 2010.[34]

The 16 occupations identified as 'high automation' tend to be those with the highest AIOE scores, both looking across all AI and for language modelling specifically (occupations appear in the top right corner of Figure 7).

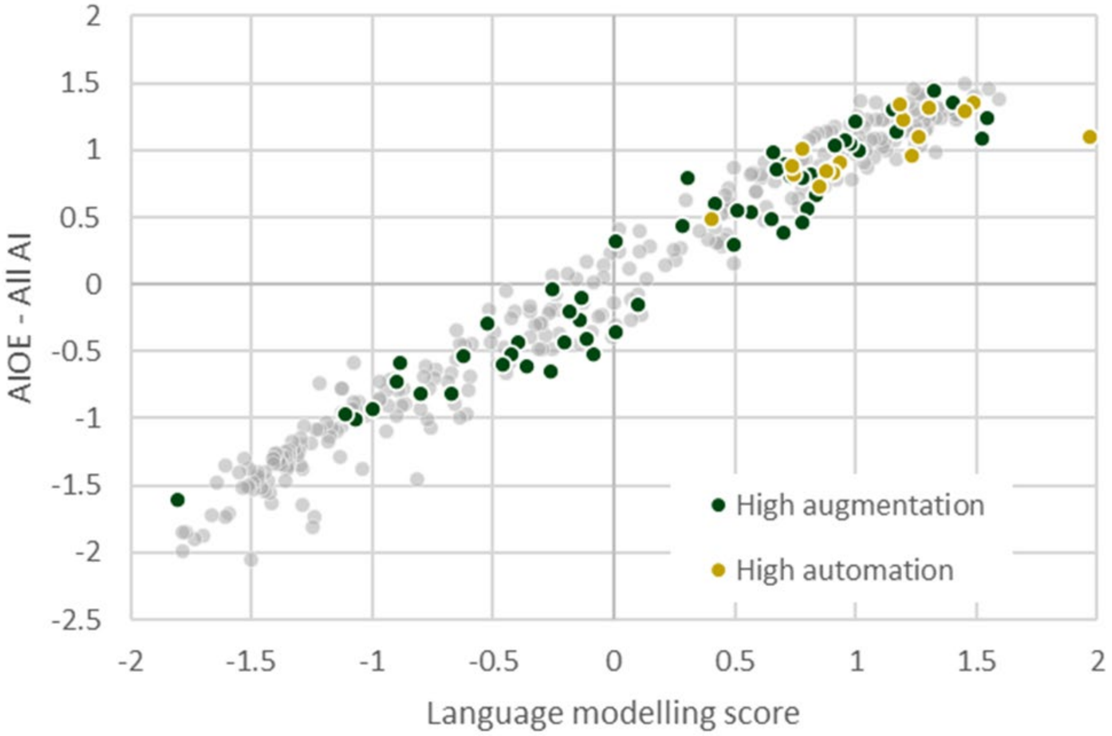
The longer list of occupations identified as 'high augmentation' have a wide range of AIOE scores, though exclude those with the very lowest AIOE scores. This is to be expected as the augmentation only refers to some, but not all, of the tasks required for a job. Further, it is possible that occupations not highlighted may still have high exposure to AI but were not able to be identified as either high augmentation or high automation.

Table 7: High automation occupations

Occupation
Authors, writers and translators
Bank and post office clerks
Bookkeepers, payroll managers and wages clerks
Brokers
Call and contact centre occupations
Customer service occupations n.e.c.
Finance officers
Financial administrative occupations n.e.c
Human resources administrative occupations
Librarians
Market research interviewers
Other administrative occupations n.e.c.
Pensions and insurance clerks and assistants
Telephone salespersons
Travel agents
Typists and related keyboard occupations

[33] Generative AI and Jobs: A global analysis of potential effects on job quantity and quality (ilo.org)
[34] Excel file for UK SOC 2010 mapped to ISCO 08

Figure 7: Occupations identified as 'high augmentation' or 'high automation' by ILO



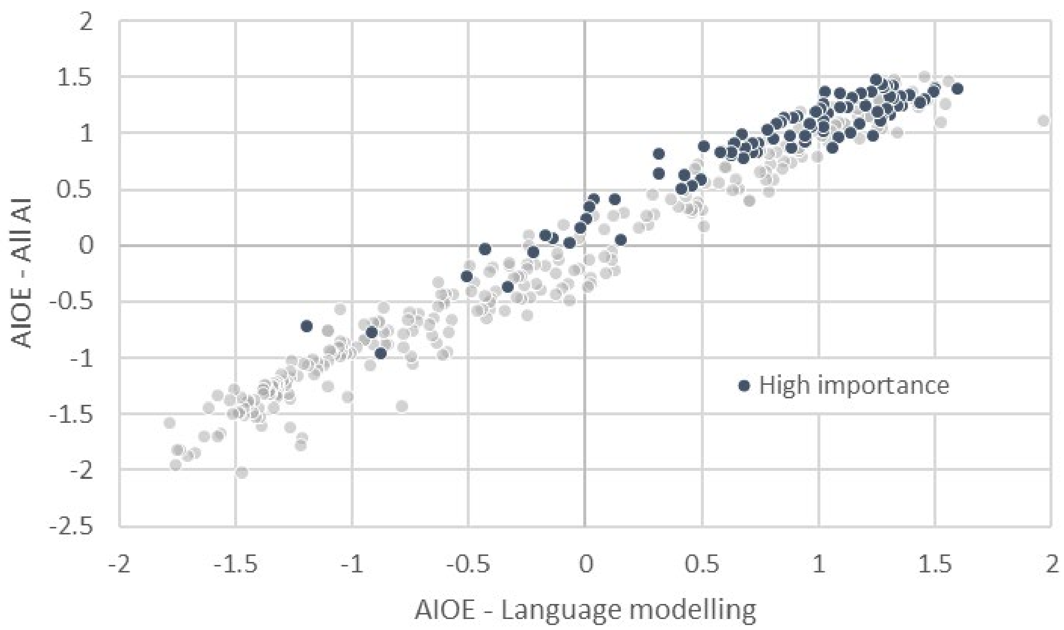
Annex 3: Comparison to findings from the Pew Research Center

The Pew Research Center produced a study in July 2023 on which US workers are more exposed to AI in their jobs[35]. This followed a similar approach to Felten *et al* but using work activities rather than human abilities. The 41 work activities listed in O*NET were classified as having low, medium or high exposure to AI based on the collective judgment of the researchers. Applying the same low, medium and high ratings to UK occupations through a mapping between O*NET and SOC 2010 allows the analysis to be replicated for UK.[36]

Occupations are ranked according to the importance and proportion of high exposure work activities, and the top quarter of occupations are labelled as AI being of high importance. The same approach is carried out for low exposure work activities.

Figure 8 shows a strong correlation between occupations with a high AIOE and occupations where AI is of high importance. The correlation to large language modelling specifically is slightly less strong but still present, and largely reflects that the Pew method considered all AI. Similarly, Figure 9 shows a strong correlation between occupations with a low AIOE score and occupations where AI is of low importance.

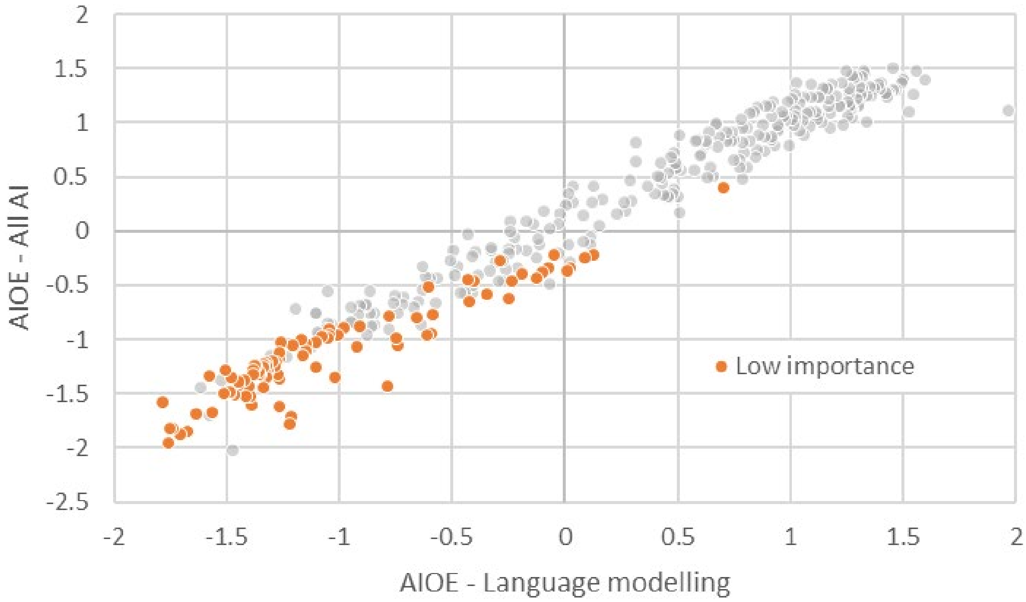
Figure 8: High importance occupations highlighted against AIOE scores for AI and large language modelling



[35] https://www.pewresearch.org/social-trends/2023/07/26/which-u-s-workers-are-more-exposed-to-ai-on-their-jobs/

[36] [UK SOC 2010 mapped to O*NET]

Figure 9: Low importance occupations highlighted against AIOE scores for AI and large language modelling



Annex 4: Further analysis for occupations exposed to large language modelling

The trends for exposure to large language modelling (LLM) follow a very similar pattern to those seen across all AI.

The estimates in this section use the AIOE scores for LLM specifically and are aggregated across industries, geography and training in the same way as described in the main report for all AI.

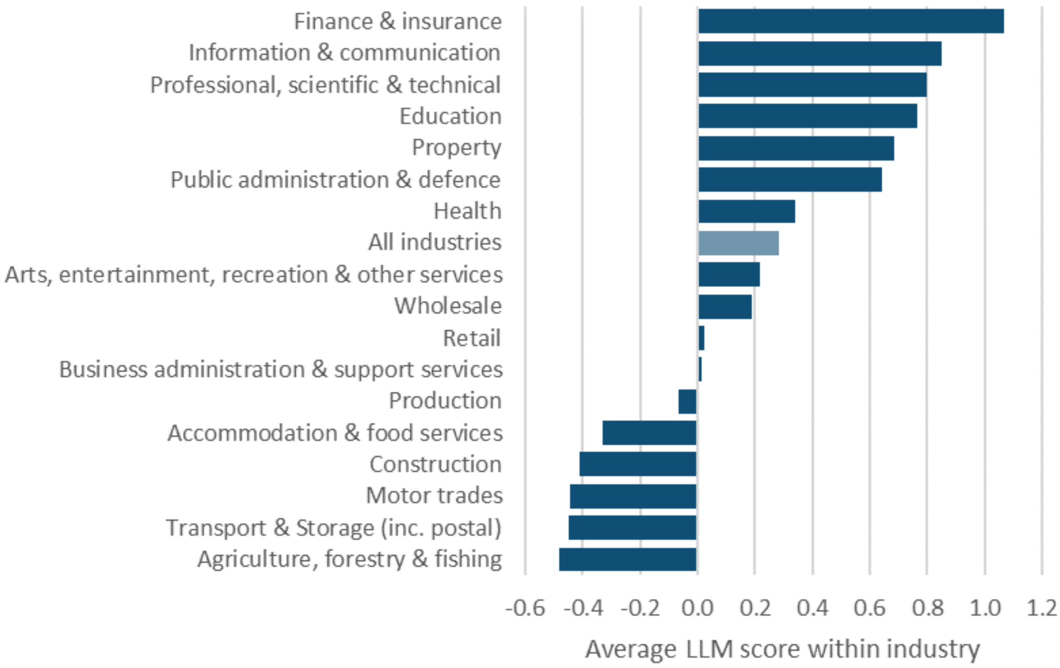
Exposure to LLM across industries

The methodology to calculate the industry estimate of exposure to LLM is constructed in the same way as is highlighted in section 3.1 for AI: taking the weighted average of the exposure scores for LLM across occupations within an industry. The average exposure to LLM for each industry is shown in Figure 10.

In general, the industries more exposed to LLM follow the same themes as discussed for AI. The top six sectors with the highest exposure to LLM are the same as those with the highest exposure to AI: finance & insurance; information & communication; professional, scientific & technical; education; property; and public administration & defence. The education sector shows slightly higher relative exposure to LLM than to AI more generally.

The industries with the least exposure to LLM are also the same as those with the lowest exposure to AI: Agriculture, forestry & fishing; transport & storage (inc. postal); motor trades; construction; and accommodation & food services.

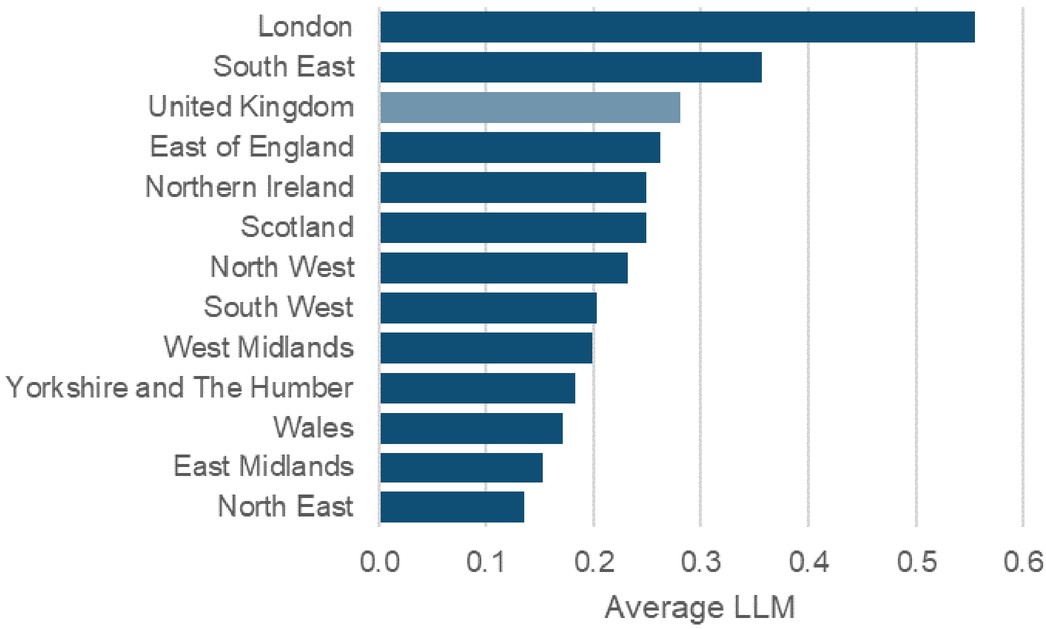
Figure 10: Exposure to LLM by industry



Exposure to LLM by geography

Figure 11 shows that similar to AI, workers in London and the South East have the highest exposure to LLM across any geographical area of the UK. They are also the only areas to be above the average for the UK as a whole. The North East is the area with the least exposure to LLM across the UK.

Figure 11: Exposure to LLM applications by geography



Exposure to LLM by qualification

Training routes

As with all AI, Figure 12 shows that learners with higher levels of qualifications are typically in jobs more exposed to LLM. The same pattern is seen overall and across different training routes.

Figure 12: Exposure to LLM by highest level of attainment for early-career employees

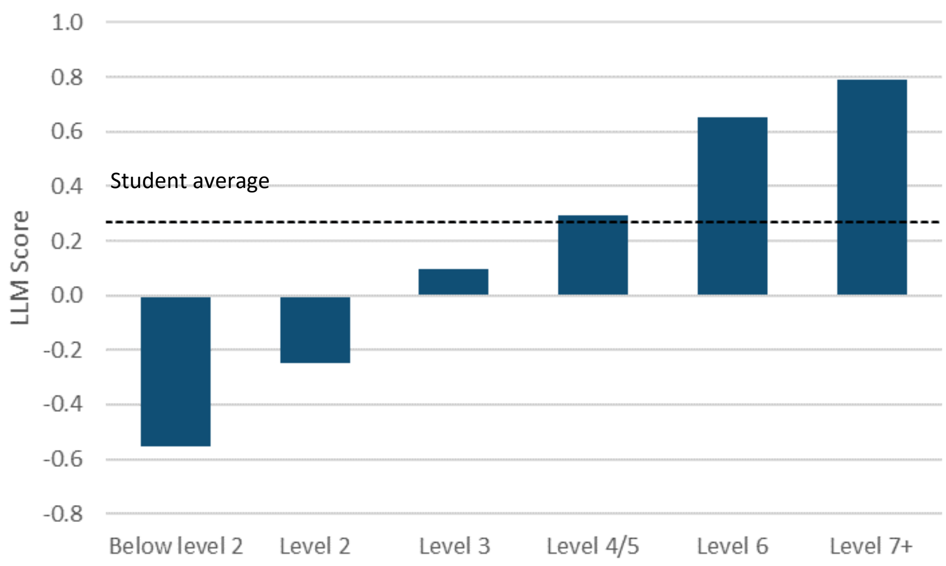
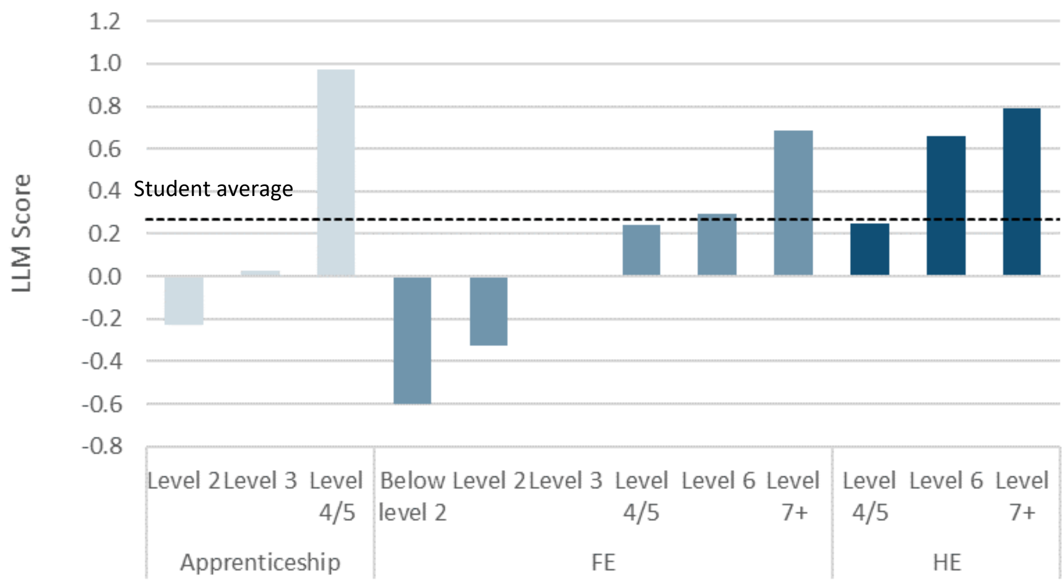


Figure 13: Exposure to LLM by training route for early-career employees



Subject areas

The tables below show more detail on the subject area for the highest qualification held by early-career employees and exposure to LLM. These show similar findings to the training most impacted by AI more generally.

Table 8: Top 5 subjects most and least associated with exposure to LLM by further education setting

	Level	Subject	AIOE
Top 5	Level 4/5	Accounting and finance	1.11
	Level 3	Administration	0.53
	Level 3	Direct learning support	0.42
	Level 4/5	Building and construction	0.36
	Level 3	Child development and well being	0.33
Bottom 5	Level 2	Transportation operations and maintenance	-0.59
	Level 2	Preparation for work	-0.61
	Level 3	Transportation operations and maintenance	-0.68
	Level 2	Building and construction	-0.71
	Level 2	Manufacturing technologies	-0.81

Table 9: Top 5 subjects most and least associated with exposure to LLM by apprenticeship setting

	Level	Subject	AIOE
Top 5	Level 4/5	Accounting and finance	1.17
	Level 3	Accounting and finance	1.04
	Level 3	Administration	0.77
	Level 3	Marketing and sales	0.60
	Level 3	ICT practitioners	0.44
…	…	…	…
Bottom 5	Level 2	Manufacturing technologies	-0.69
	Level 3	Transportation operations and maintenance	-0.81
	Level 2	Transportation operations and maintenance	-0.74
	Level 3	Building and construction	-0.83
	Level 2	Building and construction	-0.93

Table 10: Top 5 subjects most and least associated with exposure to LLM by higher education setting[37]

	Level	Subject	AIOE
Top 5	Level 7+	Economics	1.19

[37] Higher Education training has been mapped to the sector subject area classification for Further Education.

	Level 7+	Law and legal services	1.15
	Level 7+	Mathematics and statistics	1.08
	Level 6	Economics	1.08
	Level 6	Accounting and finance	0.99
Bottom 5	Level 6	Engineering and Manufacturing Technologies	0.17
	Level 4/5	Sport, leisure, and recreation	0.16
	Level 4/5	Sociology and social policy	0.15
	Level 6	Animal care and veterinary science	0.00
	Level 4/5	Engineering	-0.01

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