Associations of digital skills and earnings in apprenticeships: Empirical evidence from online vacancy data for England[1]

Stefan Speckesser*+ and Lei Xu*$

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Abstract

Despite the widespread adoption of Information and Communication Technologies (ICT) over recent decades, there is limited evidence on the utilisation of digital skills in occupations requiring mid-range qualifications and skills. However, knowing about demand for digital skills and related earnings effects from applying them would benefit learners, employers and educators alike. To gain an up-to-date picture, we processed data of 300,000+ adverts from the https://www.gov.uk/apply-apprenticeship website as an indicative source of employer demand for such skills. After creating structured data from the free text, we construct a typology of digital skills used in apprenticeship jobs and provide descriptions.

We the estimate regression models in the Mincer tradition and find positive associations between digital skills and wages in occupations requiring mid-range qualifications. There is no comparable association amongst the highly skilled jobs. A disaggregated analysis of specific skills shows that these results are driven by relatively advanced skills, while mentioning explicitly lower-level digital skills like Microsoft Office, computers, email and social media show in several specifications negative associations with observed wages.

In our view, the absence of significant estimates of digital skills in the higher-level occupations shows the endogeneity of such skills in job roles. Lower-level jobs are affected positively, but only by relatively more advanced digital skills. For the further development of apprenticeships standards in the UK, our results suggest that digital skills should extend beyond the currently included Functional Skills into the advanced skills as these would prepare apprenticeships for higher paid jobs.

Key Words: Skills/occupational choice; Returns to education; Large data.
JEL Classifications: J24, C55, I26

Corresponding author: Stefan Speckesser, S.S.Speckesser@brighton.ac.uk

Affiliations:

+ University of Brighton
* Centre for Vocational Education Research (CVER)
$ University of Bournemouth

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All remaining errors or inaccuracies remain the authors' responsibility.

Nuffield Foundation

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1. Introduction[2]

Following the widespread adoption of Information and Communication Technologies (ICT) across all sectors of the economy over recent decades, skills for accessing, evaluating, and organising information and electronic data have become vital in most occupations (Ananiadou and Claro 2009). In fact, they have become a matter of social inclusion and civic engagement more generally as access to resources, prosperity and opportunities for fulfilled lives increasingly depend on people's abilities to operate effectively in a range of digital environments. Related skills are wide ranging – from the simple use of the internet to find information, email communication and online shopping to highly specific skills such as digital content generation or software engineering. It is therefore not easy to understand the precise ways in which digital skills impact on people's lives, not even when focusing on much narrower economic outcomes, such as the effect of investing in such skills on individual earnings as suggested by human capital investment and return models. This is the main motivation for the research undertaken in this project, which was funded by the Nuffield Foundation, to explore which digital skills are applied in occupations requiring mid-level qualifications – often resulting from apprenticeship training – and whether utilisation of digital skills give rise to positive earnings effects.

While a number of frameworks have been developed conceptualising such skills, such as the Digital Competence framework for Citizens ("DigComp 2.1", see Vuorikari *et al*., 2016), the UK's "Digital Capabilities framework "(Jisc, 2016) and an "Essential Digital Skills Framework" by DCMS/DfE/Lloyds, there are only a few studies on the empirical earnings effects of digital skills making use of such conceptualisations, which provide systematic and exhaustive descriptions how/where digital skills are affecting occupations (Kispeter 2018). This likely results from the difficulty of operationalising the comprehensive skills frameworks into measurable quantitative indicators and from a lack of systematic data available to describe the specific skills involved as well as their level of proficiency and specialisation.

Instead, most of the empirical estimates of earnings impacts make use of available research surveys and provide evidence of the impact of digital skills on earnings or other economic outcomes (e.g. Falck et al., 2022) conditional on other characteristics such as formal levels of education. A second strand of research focusing on the impact of digital skills on social inclusion makes use of similar data (e.g. van Deursen and van Dijk, 2015). Both strands are restricted to digital skills being covered in such data, which have come from self-assessment or performance tests carried out in population surveys or specific research surveys such as the OECD's the Programme for the International Assessment of Adult Competencies (PIAAC) and thus make use of data on labour supply.

Our research engages with this literature, but instead of using existing data sources, we have created new data to explore and describe digital skills based on online vacancy data. This research design was motivated by our objective to understand skills involved in specific occupations, i.e. labour demand, rather than skills investment by individual workers, a measure related to skills supply. In addition, vacancy data also offer the most up-to-date information, which is an important consideration as digital skills continue to evolve with technology, the use of mobile devices for specific tasks, improvements of internet speed and availability of cloud-based services. Initially based on webscraping of the UK Governments website with apprenticeship offers (https://www.gov.uk/apply-apprenticeship) and later based on a Freedom Of Information Act (FOIA) request, we created a database of 433,799 online vacancies, which we analyse in the following.

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We use the Apprenticeship vacancies to create an empirical dictionary of digital skills, which we apply using text mining methods to obtain a systematic description of digital skills involved in different types of apprenticeships (level of education, sector). In addition, a supplementary dictionary was created making use of the regulation of the occupational standards ("Apprenticeship Standard") in apprenticeships identified as in the "Digital route" by the Institute for Apprenticeships and Technical Education. Using this dictionary, we describe how widespread skills from apprenticeships explicitly understood as "digital" occupations are across all jobs requiring mid-level qualifications. Both dictionaries are used to provide descriptions of the prevalence of digital skills and were included in regression models explaining wage differentials related to digital skills. Because the vacancy data are recent (August 2018 – November 2021), we also provide a brief description about recent change of digital skills demand following the Covid-19 Pandemic, however, this description shows only very small change.

As apprenticeships are jobs with training, the related occupational standard documents allow for consistent linkage to the UK's Standard Occupational Classification (SOC). Although recent apprenticeship reform enabled employers also to fund university degrees as part of the education (and in fact such programmes have grown a lot in recent years), the link to SOC Codes show that most Apprenticeships are still related to occupations at the mid-range of skills, which require a Level 3-5 education, i.e., Administrative and Secretarial (SOC 4); Skilled Trades (SOC 5); Caring, Leisure and Other Service Occupations (SOC 6).

We focus on the description of digital skills involved in apprenticeships based on the two dictionaries applied to conceptualise digital skills. We provide descriptions of the data by structural characteristics and whether any changes follow after the Covid-19 Pandemic. We then employ Mincer-type regression models to investigate three research hypotheses (H1-H3):

> H1: There are positive wage differentials associated with digital skills.
>
> H2: Associations of wage differentials differ by SOCs and mid-skills jobs show the greatest impact of digital skills.
>
> H3: Higher-level skills drive the overall wage returns; some basic digital skills have become the norm and by explicitly requesting them in job adverts, they are associated with lower-level job roles and lower earnings.

Finally, we estimate models linking aggregations of our online vacancy data at three-digital SOC-Level to the Annual Survey of Hours and Earnings (ASHE) at individual level. Our regression models exploit the variation within larger SOC-1 groups to estimate returns to digital skills at SOC-1 level while conditioning on further characteristics, such as gender, age, work experience and formal level of education. With ASHE data being representative for overall labour demand in the UK and covering all age groups, these models allow for an approximation of life-time returns to digital skills involved.

Findings

We find that digital skills are associated strongly with professional and associate professional occupations, especially skills to operate general/professional software, and computing languages. At mid-range skills, administrative and secretarial occupations require predominantly Microsoft skills as well as data and computer skills. For caring, leisure and service occupations, we find some demand for computer skills, while sales and customer service occupations involve mainly digital related and data skills. We don't find strong requirements for digital skills in managerial roles, perhaps the key skills required by managers are more conceptual and thus less specific than can be captured by the framework developed here.

Based on findings from the wage regressions, which exploit the variation of the incorporation of digital skills in the vacancies within each three-digit SOC occupation, we find significant and positive associations between digital skills and wages in lower-level occupations, especially among administrative, skilled trades, and elementary jobs. There is no comparable association in the highly skilled qualifications. A disaggregated analysis of specific skills shows that these results are driven by relatively advanced skills, while mentioning explicitly lower-level digital skills like Microsoft Office, computers, email and social media in many specifications exhibit negative associations with observed wages.

In our view, the absence of significant estimates of digital skills in the higher-level jobs shows the endogeneity of such skills in occupational roles. As lower-level jobs are affected positively – but only by the relatively higher digital skills – general and vocational education should aim to provide such skills to allow people at mid-range skills to benefit from the related earnings premium. However, the negative effect found for basic digital skills suggest that skills investment must be significant and go beyond certification of basic computer literacy, which are primarily involved in apprenticeship training, such as Functional Skills for ICT at Level 2 or below.

The rest of this paper is structured as follows: In part two below, we describe the policy context and recent regulatory change affecting apprenticeships in England and how participation in these programmes developed. Part three reviews the literature on digital skills, describing key conceptualisations as well as findings about digital skills included in apprenticeships and related evidence on earnings differentials associated with them. In part four, we develop an empirical framework to measure the extent to which digital skills are being used in apprenticeships. In part five, we provide extensive descriptions of the data in relation to our research hypotheses and then estimate linear models on wage differentials related to digital skills in part six. Part seven summarises key findings and concludes.

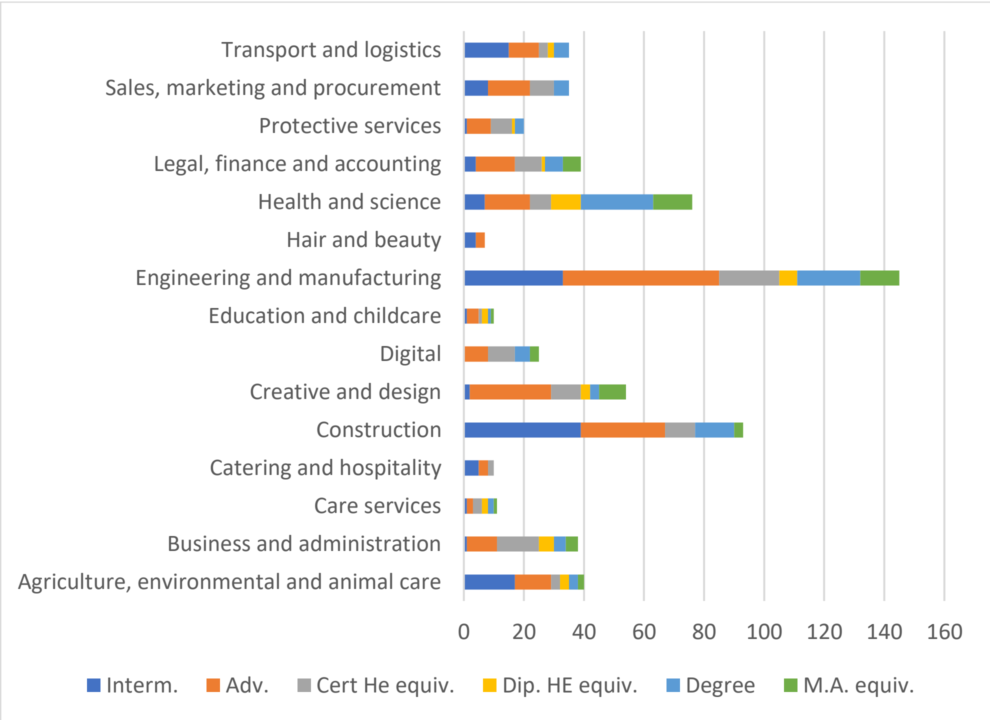
2. Background to apprenticeships in England

As has been the case historically across much of Europe, apprenticeships in England offer a versatile training, which allows employers to train new and existing staff according to their skills requirements, while apprentices are (mostly) in permanent employment and obtain related salaries. Modern apprenticeships were introduced in the UK in the 1990s. Initially not very successful, various regulatory changes aimed to improve their attractiveness as an education and skills programme: First, with the introduction of the Apprenticeships, Skills, Children and Learning Bill in 2009, apprenticeships were enhanced by including recognised qualifications relevant for their occupations and – where needed – remedial English and mathematics education to level of good secondary school attainment. Most of apprenticeships were at Intermediate Level (Level 2) preparing people for semi-skilled roles and relatively fewer were at Advanced Level (Level 3) or above. The average duration of Intermediate Apprenticeships was around 12 months for most programmes and the majority were completed within 24 months (Bursnall et al, 2017).

Continued reform changed the nature of apprenticeships in recent years: First, the introduction of “Apprenticeship Standards” from 2015 transferred the development of education and qualifications to employers, while a new “Institute for Apprenticeships and Technical Education” was set up to regulate occupations covered in apprenticeships. Employer leadership resulted in a large increase of apprenticeships, many of them involving higher education or even university degrees. In another reform, the government introduced an “Apprenticeship Levy” in 2017, requiring larger employers to contribute 0.5% of their pay bill in excess of three million pounds into a reserve account, which can only be used to pay towards the tuition fees of accredited apprenticeships.

Because of these recent reforms, apprenticeships became recognised qualifications across the full range of skills and occupational roles, see Figure 1. As of November 2021, there are 638 programmes operating from more than 755, which have been created since 2015 (some of them still being developed or already retired)[3]. A breakdown by the sectors or “routes” shows wide differences by industries: While some large sectors like hair and beauty, catering and hospitality, care services and education and childcare only have around 10 programmes, there is much more variety e.g. in engineering and manufacturing (145 programmes), construction (93 programmes) and agriculture (40). Amongst the professional services, a wide range of programmes can be found in health and science (76 apprenticeships), business and administration and legal, finance and accounting (~40 each) as well as sales, marketing and procurement (35) and transport and logistics (35).

Figure 1. Number of operating Apprenticeship Standards and levels.



Source: Institute for Apprenticeships and Technical Education (download 11/11/2021)

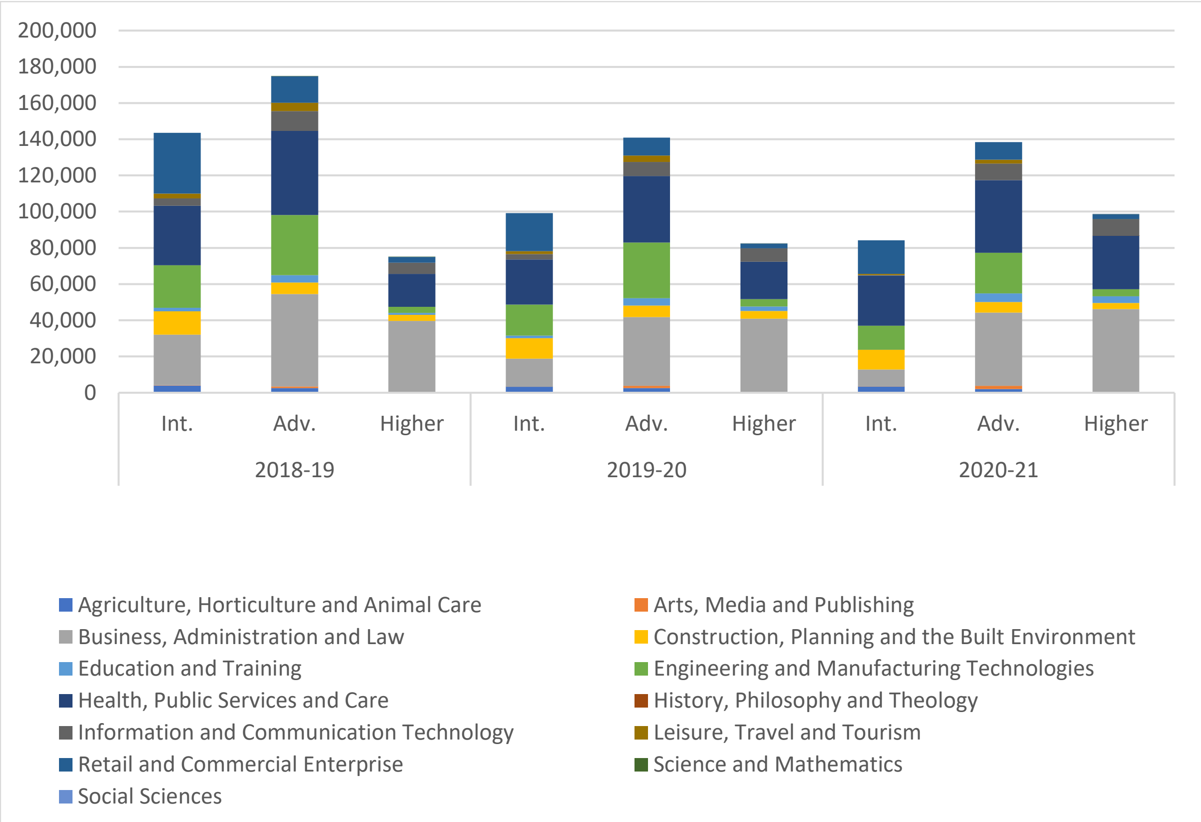
Looking into the official statistics of apprenticeship starters (Figure 2), we find noticeable decline following the Covid-19 Pandemic: Apprenticeship starts are down by around 18% in both 2019/20 and 2020/21 academic years compared to 2018/19, but the decline affected different levels of apprenticeships to a varying extent: Intermediate Apprenticeships are 41% below the level of 2018/19, while the decrease was only half that for Advanced Apprenticeships (-21%). Apprenticeships including tertiary education even increased by 32%.

Among the Intermediate Apprenticeships, there were very large declines observed in business and administration (from 27,900 in 2018/19 to 9,390 in 2020/21) and engineering (2018/19: 23,550 and

[3] Data as of 11/11/2021

2020/21: 13,250) in both years of the Covid-19 Pandemic. Compared to this, Advanced Apprenticeships declined in the first year of the Pandemic. Overall, the data show a shift to higher-level apprenticeships and sectoral change: In 2020/21, Higher Apprenticeships represented 31% of the total, up 12 percentage points compared to 2018/19. The increase was specifically strong for Health, Public Services and Care Occupations (from 20,630 in 2018/19 to 29,480 in 2020/21) and Information and Communication Technology (from 7,400 to 9,180 in the same time period).

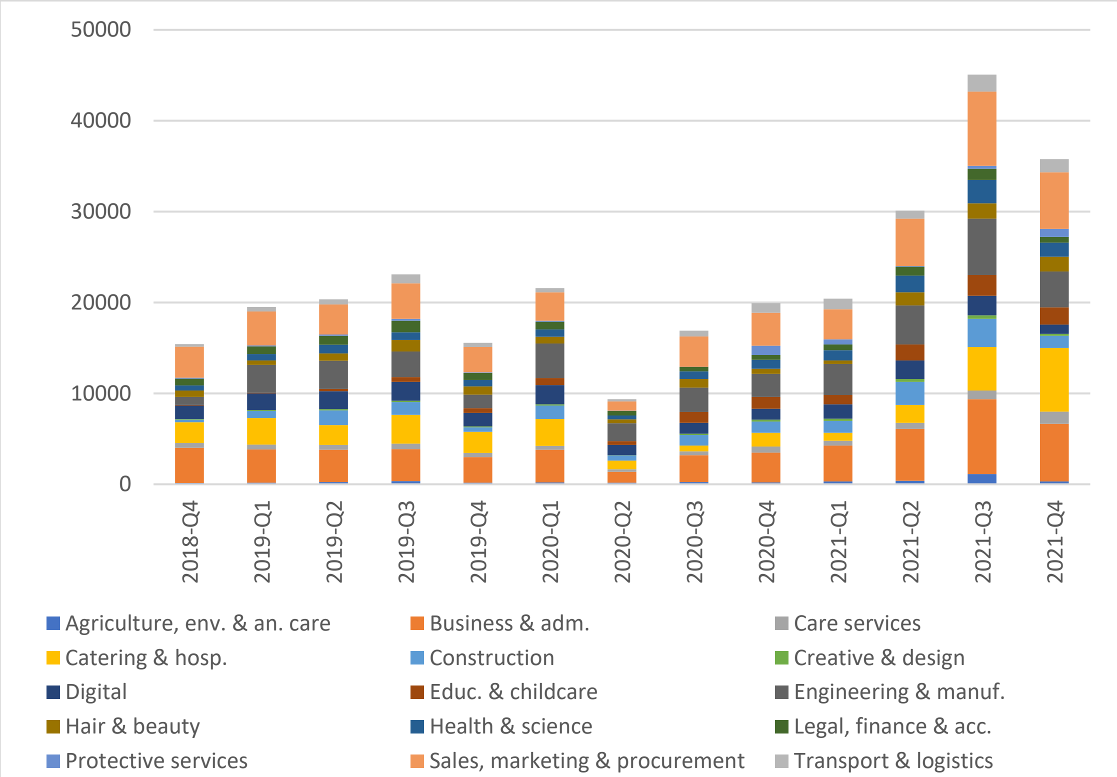
Figure 2. Number of apprenticeships started in recent years and by levels.



Source: Apprenticeships and traineeships statistics (https://explore-education-statistics.service.gov.uk/find-statistics/apprenticeships-and-traineeships/2020-21) downloaded 15/02/2022

A look into the vacancies advertised since August 2018 (Figure 3), which we use in the empirical analysis later on, shows the development before, during and after the Covid-19 Pandemic. While the jobs advertised only represent about a third of the actual apprenticeship started later on – due to a some not being advertised and a large number of apprenticeships taken by existing staff without further advertisement (see Xu and Speckesser, 2022) – Figure 3 shows the impact of the Covid-19 Pandemic with more recent data than statistics of starters, which usually lag behind for a few quarters.

Figure 3. Number of apprenticeship vacancies by closing dates (in quarters) and routes.*



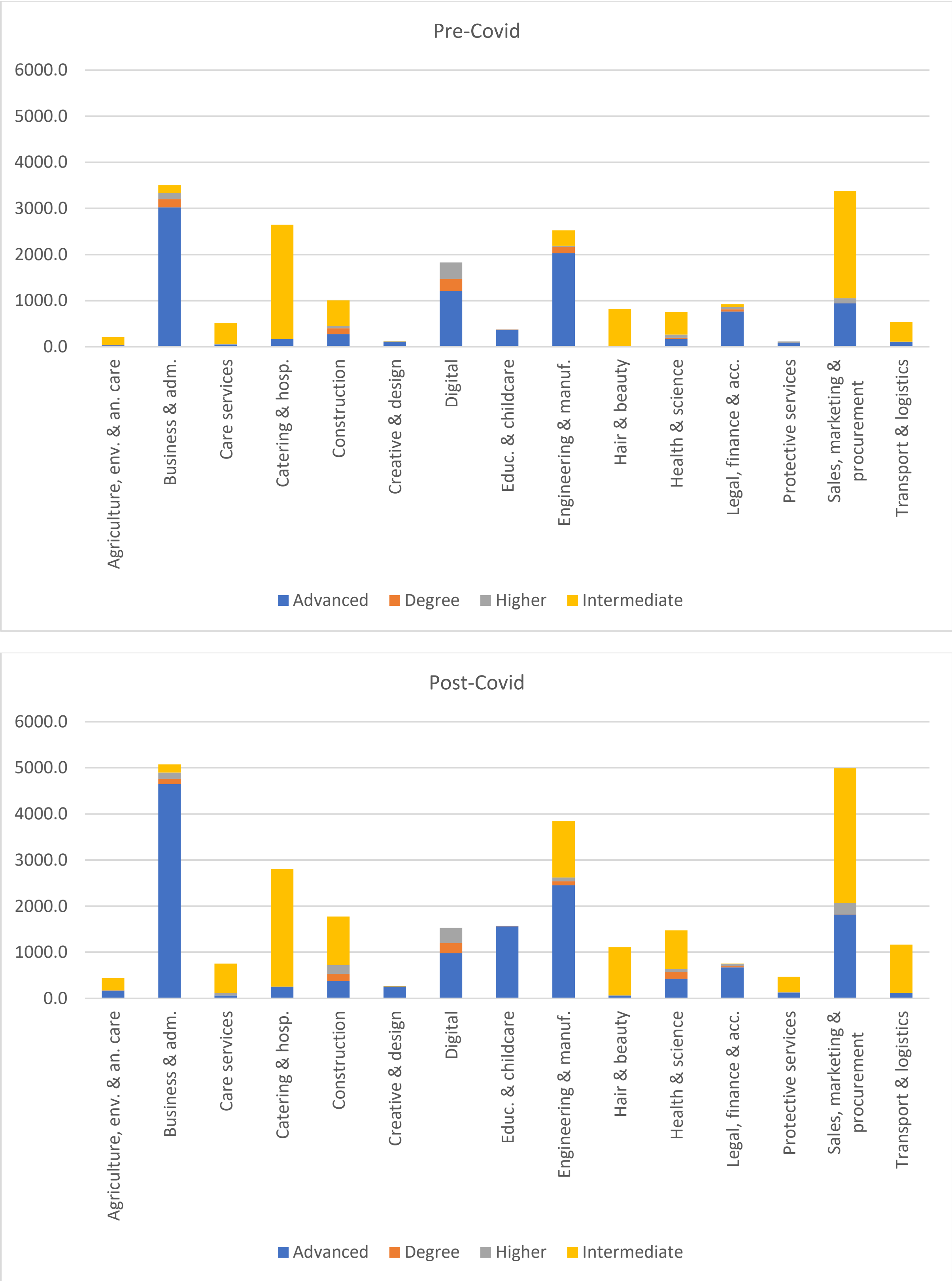
* Excluding apprenticeships not yet aligned to Apprenticeship Standards
Source: https://www.gov.uk/apply-apprenticeship.

As can be seen in Figure 3, there was a growth of about 46% on average for the vacancies closing after/including Q3/2022 (on average 28,026 per quarter) compared to before the Covid-19 Pandemic (Q4/2018 until/including Q1/2020, 19,250). Within this growth, education/childcare and protective services (i.e., the police) grew strongly, this likely results from new apprenticeship standards becoming operational in the public sector and a requirement to spend the apprenticeship levy accumulated over recent years. In other sectors, apprenticeships are levelling, e.g. catering and hospitality (+6%) or decreasing like digital and legal/finance/accounting, which are 15-20% below the level before the first lockdown.

In addition to the sector change, Figure 4 shows that apprenticeship vacancies are also increasingly at higher-levels of education: Advanced and Higher Apprenticeships (involving tertiary education below degree level) increased, especially in business and administration, sales/marketing and procurement and engineering, while Intermediate Apprenticeship vacancies grew less/declined. Some routes offered few or no Intermediate Apprenticeships (e.g. education/childcare and digital), while protective services saw new apprenticeships at this level emerging in recent years.

In summary, the statistics on apprenticeship starts as well as the description of vacancy data represent the recent and continued changes affecting apprenticeships, which are increasingly at higher skills levels and in the sectors traditionally not operating such programmes. In the further analysis, we link all vacancies to the Standard Occupational Classification systematic (SOC), which shows that apprenticeships now represent the full skills spectrum, from low skilled operational roles up to professional and managerial occupations (SOC-3).

Figure 4. Quarterly average number of vacancies by routes and levels, pre- and post-Covid-19 Pandemic (up-to/including Q1/2020 and from/including Q3/2020).



* Average quarterly vacancies (by closing date), excluding those not aligned to Standards
Source: https://www.gov.uk/apply-apprenticeship.

3. Literature review

Conceptualisations of digital skills

Looking into digital skills in apprenticeships first requires a working definition of what is covered when talking about them. Various conceptualisations evolved in recent years: While first definitions of digital skills focused on technical knowledge about computers, over time definitions further included cognitive, attitudinal, social, and emotional skills (Ala-Mutka, 2011).

In the academic literature, a wide range of different and overlapping conceptualisations can be found, which in addition to digital skills describe digital capabilities, digital intelligence, digital fluency, computer literacy, internet literacy, media literacy and digital literacy. A recent UNESCO report states that there is no one set of agreed definitions for digital literacy as literature refers either to digital 'skills', 'competences' or 'aptitudes' as well as 'knowledges', 'understandings', 'dispositions' and 'thinking' (Broadband Commission for Sustainable Development, 2017, p.23).

With the evolving digital landscape, different digital literacy models and frameworks have been produced to define the nature of digital literacies. Exploring the 'digital literacy' movement, Mark Brown (2017) explains that

> 'what we define or understand as digital literacy is messy and far more problematic than reflected in most of the current flashy, flimsy and faddish frameworks.'

The different frameworks provide different conceptual maps for competences aiming at defining the nature of digital literacies. But there is no single set of competences that is suitable for all. Although it is possible to identify generic digital skills across a wider population, any definition of digital skills is related to a specific context, timeframe and group of individuals.

A systematic literature review by Van Laar et al. (2017) explored digital skills in the context of workforce preparation and particularly looked at the concepts being used to describe the skills needed in a digital environment. Across the 75 studies reviewed, this paper presents a conceptualisation of seven core skills focusing on digital dimensions, and five further contextual dimensions. All skills involved were seen as fundamental for performing tasks in a broad range of occupations. Core skills were identified to include: 1) Technical skills; 2) Information management; 3) Communication; 4) Collaboration; 5) Creativity; 6) Critical thinking and 7) Problem solving. In contrast, contextual skills covered 1) Ethical awareness; 2) Cultural awareness; 3) Flexibility; 4) Self-direction, and 5) Life-long learning.

Frameworks of digital skills tend to cluster skills into broad dimensions covering different areas of interests and focus on competences needed in a range of roles and contexts. For example, the Irish All Abroad! project (2015) created frameworks and models of 'skills for the digital age' in the context of higher education (Sime and Themelis, 2019).

From the diversity of conceptualisations reviewed, we find that three comprehensive frameworks on digital skills across varying levels of proficiency:

1. The first framework, Digital Competence framework for Citizens DigComp 2.1 (Vuorikari *et al*., 2016) identifies five key areas of digital competence — 1) Information and data literacy; 2) Communication and collaboration; 3) Digital content creation; 4) Safety, and 5) Problem solving. There are 21 related competences and eight proficiency levels (Carretero *et al*., 2017). According to this framework, being digitally literate means 'Using digital technologies in a confident and safe way for various purposes such as working, getting a job, learning,

shopping online, obtaining health information, being included and participating in society, entertainment, etc. While the development of this comprehensive framework has been useful to standardise digital literacies, questions have been raised on the flexibility and agility to contextual differences (Brown, 2017).

2. The second example of a widely cited conceptual framework, the UK's Digital Capabilities framework was designed to be 'used by staff in any role and by students in any educational setting'. The framework clusters digital capabilities into six broader elements:

    - Information and communications technology (ICT) Proficiency (functional skills).
    - Information, data and media literacies (critical use).
    - Digital creation, problem solving and innovation (creative production).
    - Digital communication, collaboration and partnership (participation).
    - Digital learning and development (development).
    - Digital identity and wellbeing (self-actualising).

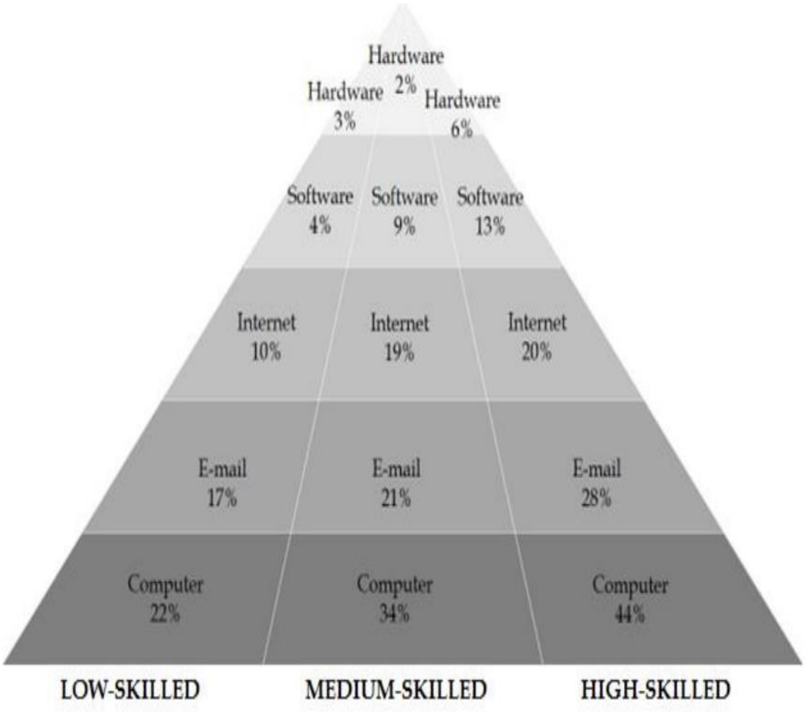
    It also includes 15 sub-elements which are a combination of functional skills, critical use, creative production, participation, development, and self-actualising (Jisc, 2016). The framework acknowledges the contextual dimension incapsulated in the definition of what it means to be digitally literate by describing digital literacies as 'a set of situated practices supported by diverse and changing technologies' (ibid.).

3. Finally, the Essential Digital Skills Framework[4] used by DCMS/DfE/Lloyds defines digital skills needed to participate and contribute to the current digital world by splitting digital skills into foundational, essential skills for life and work. 'Foundation' skills refer to those typically required by people not currently using digital technology or using it in limited ways. The framework identifies five categories of Essential Digital skills for life and work: 1) Communicating; 2) Handling information and content; 3) transacting; 4) Problem solving and 5) Being safe and legal online.

In addition to conceptual frameworks, we reviewed an empirically derived categorisation making use of vacancy data (Beblavý et al. 2016), which describes digital skills as a pyramid. This concept considers the formal level of skills required for a job vacancy (low, medium and high skills) and then works across a range of keywords identified within the skill levels (computer skills, software, hardware, internet or web, email and outlook, etc.), which are then clustered in wider groups of digital skills. As shown in Figure 5 below, there is an increasing use of different digital skills as formal skill levels increase.

[4] https://www.gov.uk/government/publications/essential-digital-skills-framework/essential-digital-skills-framework

Figure 5. IT Skill pyramid.



Source: Beblavy et al. (2016).

As was described in a recent study commissioned by DCMS reviewing the different definitions of digital skills, extant conceptualisations of digital skills are broadening out and increasingly overlap and with other concepts such as computer literacy, internet literacy, media literacy, digital literacy and encompassing different types of skill sets (Ecorys, 2016).

In our view, none of the currently used frameworks on digital skills can be operationalised into clearly defined quantitative measurement of digital skills involved and/or a way to compare specific skills across a range of occupations, not even in some of the clearer sub-categories such as problem solving. This results from a lack of specificity of skills and a missing link to formal levels of qualifications, which represent available measures for proficiency levels in education and occupational skills demand. It is also difficult to understand how non-digital skills capturing crucial elements, such as problem solving or planning, can be separated from them.

As a consequence, we suggest a data-driven approach obtained from mining the available apprenticeship vacancies. We use frequencies in text documents in order to derive subjects and hierarchies of IT-related skills in job adverts or from the analysis of Apprenticeships Standard documents for apprenticeships from the "digital" route. Both approaches of text mining result in dictionaries used for a quantitative text analysis, which we use to derived quantitative measures of digital skills, which can be compared across apprenticeships in different sectors and at different formal level of qualification.

Review of economic and wider impact of digital skills

In addition to empirical frameworks, we also reviewed the literature on the social and economic impacts of digital skills deals, which aimed to obtain evidence on the economic benefits and more narrowly the empirical earnings differentials associated with digital skills. We had envisaged to obtain a literature body to provide a review of the estimates of earnings differentials associated with mid-range skills jobs, but then we realised that quantitative research around such impacts is still very limited.

Based on quite extensive search of available literature databases within EBSCOhost[5] and JSTOR, we found that available academic research about quantitative impacts of digital skills is concerned with main aspects:

- First, there is the problem that digital skills are adopted and used differentially across the society, resulting in new or reinforced inequalities in access to resources and prosperity. This literature can be summarised as focusing on the "Digital divide" and how it can be overcome to achieve digital inclusion.
- Then, there is a second strand of literature, which focuses on the impact of digital skills on labour productivity and earnings ("Economic impact of digital skills") and consequently with barriers to the adoption and optimal use of digital skills in production.

Both strands of literature make use of available survey data on digital skills, which are either coming from self-assessment surveys or performance tests (see Allman and Blank 2020). Such research instruments ask a representative sample of the population about tasks performed in the workplace, which can relate to certain skills undertaken and allow to obtain inference on the impact of digital skills. In addition to such measures, as for example included in the Current Population Survey (CPS) for the US (e.g. Krueger 1993), many surveys capture a range of workplace and personal characteristics, specifically formal levels of education, to provide estimates on the differential impact of digital skills. Alternatively, as used in Falck et al. (2021), international surveys like the Programme for the International Assessment of Adult Competencies (PIAAC) across 19 countries capture digital skills via a complex set of performance related tests. Respondents in PIAAC are asked to find solutions to problem sets included in the survey, which focus on the use of ICT-based applications such as an Internet browser and web pages, e-mail, word processing, and spreadsheet tools (see ibid., 3). One of the key difficulties in both these concepts is that digital skills are not time invariant and evolve reflexively with the progression of both hardware and software technology (Magee et al. 2017), rendering evidence based on historic studies, for example on the ceteris paribus impacts of computer use on wages at given levels of education, largely obsolete, as digital skills are no longer comparable to data from the 1990s. This problem has accelerated with the increasing use of mobile devices and cloud-based services, which reduce the deployment e.g. of skills required to organise and store data.

In terms of the research evidence around digital inequality/digital inclusion over the last few years there is wide agreement that the use of technology, including skills and usage "reinforce existing inequalities, as human capital carries over to the online world" (van Deursen et al. 2021, Information, Communication & Society). This is specifically relevant if the use of digital skills is no longer optional as e.g. the use of the internet has become the default for many, including government services (Allmann and Blank 2020), but these skills are unevenly distributed across society. While this is changing over time, certain social groups remain less likely to make full use of technology. These changes observed over time also affect different skills: Based on longitudinal data, van Deursen and van Dijk (2015) show highest relative growth in operational and formal internet skills, while information and strategic internet skills remained relatively constant. In the same study, gender, age and educational background are found to be important drivers in

[5] British Education Index, Business Source Premier, eBook Collection (EBSCOhost), Education Abstracts (H.W. Wilson), Educational Administration Abstracts, E-Journals.

inequalities, indicating that opportunities from the digital society differentially benefit groups with higher education and higher socio-economic status.

Focusing on the impact of the Internet of Things (IoT) on digital inequality, a further study by Van Deursen et al. (2021) suggest that the extension of digital technology into the IoT (i.e. physical objects making use of digital technology to connect and exchange data over the internet) likely increases the digital divide. Similar, Korovkin et al. (2022) emphasize the role of (other) human capital driving inequality, but less so income, in line with Huang and Chen (2010) showing GDP per capita becomes less important over time in explaining digital adoption. Extending from this result, the authors conclude that "while digital divide was rooted in other inequalities, it cannot be reduced to them (…) technology is an important independent factor (…) amplifying some inequalities (skills and competencies) and moderating others (income)" (ibid.). This study also includes evidence on the key role of policy to reduce digital inequality.

The research evidence around the impact of digital skills on productivity and earnings has a much longer history, dating back to the "Solow paradox", which refers to the observation that despite the extensive adoption of digital technologies in the 1970s and 1980s, productivity growth in the U.S. and other countries slowed down compared to the post-war years. The empirical literature on the impact of ICT on economic growth and factor productivity has since evolved, see e.g. Draca, et al. (2006), evidencing a strong, if not dominant role of ICT investment on growth, based on a review of empirical studies using micro and macro-economic data, especially for the U.S.

A recent summary of the literature related to the impact of technology on employment and earnings rather than the aggregate productivity can be found in the Handbook of Labor Economics, Chapter 12 (Acemoglu and Autor, 2011). This chapter provides a model describing the key mechanism of improving technologies, including ICT, to be factor-augmenting across the different skills groups (low skill/high skill) that perform different and imperfectly substitutable tasks or produce two imperfectly substitutable goods. By affecting the various types of labour differentially, ICT investment changes both demand and supply of the different groups. Empirical research based on the model successfully explained the growing demand for skilled labour in the U.S. and – by nature of increased returns to higher education – the increasing inequality observed in the wage distribution by skill groups and hence the polarisation of employment, see Acemoglu and Autor (2011).

Based on a task-based approach (i.e. a unit of output produced by a worker), which can be linked back to differential skills (i.e. the capabilities to undertaken specific tasks), the authors argue that the "relative demand for skills increases over time because changes in technology are assumed to be 'skill biased', in the sense that new technologies have greater skill demands for or are more complementary to high skill workers." (Ibid., 1098), explaining positive wage effects for high-skilled labour resulting from technological investment and the growing college wage premium. These findings are in line with empirical studies, e.g. Gaggl and Wright 2017, who find that ICT investments complement non-routine, cognitive-intensive work.

In terms of the analysis of empirical returns to investment in digital skills more narrowly, a variety of studies have been published over recent years making use of extensions of the standard Mincer model of returns to human capital investments. The empirical findings from most studies show significant positive wage returns to digital skills, which are either regarded as ICT skills (Dolton and Makepeace 2007) or computer use (Krueger, 1993; Felstead, et al. 2007). These returns remain significant in models aiming to remove unobserved heterogeneity that might affect job-related computer use and earnings. Studies focusing on skills rather than the use of computers, i.e. self-reported computer knowledge or skills cast doubt on the existence of wage returns to computer use or skill, either by suggesting that other skills (pencil use/telephones) are creating similar returns (DiNardo and Pischke, 1997) or by finding that using a computer has no substantial impact on wages (Borghans and ter Weel, 2004).

Focusing on specific skills, DiMaggio and Bonikowski (2008) find significant positive effects of Internet use on earnings growth, suggesting that "some skills and behaviors associated with Internet use were rewarded by the labor market". The positive association appears to reflect the effect of Internet use, rather than use of computers for offline tasks. Therefore, the access and effective use of the Internet matters to overcome to digital divide.

Similar, Falck et al. (2021) find statistically significant positive returns to ICT skills of a magnitude in line with wage impacts of other cognitive skills, such as numeracy skills, and quantifies the impact of a change in ICT skills by one standard deviation to lead to an increase in earnings of 24 percent. A key mechanism for the high wage returns is the selection into occupations with high abstract task content, allowing workers with high ICT skills to benefit from the wage premia these jobs pay (ibid., 14). A central finding from this study is that ICT skills can be promoted by providing access to ICT infrastructure, the skills return suggests that public policy improving access to ICT access will be effective to mitigate some of the digital divide, allowing disadvantaged groups to benefit from the substantial wage returns to digital skills. The impact of the specific nature of digital skills has been discussed in a recent paper by Eggenberger and Backes-Gellner (2020), providing evidence on the positive impact of generic IT skills on earnings after involuntary separations, compared to negatively correlated earnings after for IT experts. A macroeconomic study on the relationship between digital skills and employment outcomes based on PIAAC data provide some descriptive evidence on the correction of these variables, see Bejakovic and Mrnjavac (2019). Based on data for Germany, Wild and Schulze Heuling (2020) compare the digital competences among students of cooperative education and vocational training students, showing that students in cooperative higher education institutions have more advanced digital competences than those in vocational training programmes. Like Tenberg and Pittich (2017), this study provides evidence on the differential adoption of digital skills and likely impact on earnings for people with mid-range skills.

There is no doubt that the recent technological developments have enlarged the conceptualisation of digital skills, including generic digital-related skills, digital platforms and devices, etc. By combining Italian Labour Force Survey and data with measures of digital related tasks, Cirillo et al (2021) conclude that high-skilled occupations demand high level of digital skills and jobs demanding more digital skills grow faster than others. They also argue firms may digitalise jobs with substantive amount of routine tasks to improve efficiency and save labour costs, consequently resulting in job loss. On the other hand, in a qualitative work by Lloyd and Payne (2021), the authors argue although digitalisation or automation may replace lower-level occupations, workers are still required to oversight and intervene, casting doubt on the potential massive job loss.

Digital skills in occupations with mid-range skills and apprenticeships

To the best of our knowledge, there is limited systematic quantitative evidence about the use of specific digital skills in occupations with mid-range skills, i.e. jobs often accessed via apprenticeship programmes. Here, we define mid-range skills as jobs, which require a completed vocational education (i.e. Level 3 in the British education system) or a post-secondary education below degree level (Levels 4-5), and which map in the Standard Occupation Classification (SOC) to skilled Administrative and Secretarial (SOC 4), Trades (SOC 5) and Caring, Leisure and Other Service Occupations (SOC 6). Much of the current evidence for such jobs has been published in studies published by Cedefop.[6] The studies show widespread application of digital skills across the economy with office software, programming and processing the top three ICT skills, while the most important digital skills more widely refer to computer use, digital tools for collaboration and managing digital data.

Another study by Cedefop (2020) based on desk research and focus groups with a comparatively large number of interviews shows evidence that initial vocational education towards mid-range skills includes digital skills in all EU Member States, Iceland and Norway and the UK. Many education programmes work towards common standards like the European digital agenda, e-competence, DigCompOrg, the European computer driving licence (ECDL), and the Council recommendation on key competences for lifelong learning. At this basic level, programmes like ECDL are covering skills such as IT security, IT fundamental and the use of email and internet. Even in its most advanced level, the ECDL mainly covers Office applications. ECDL is similar to the ICT skills included in apprenticeships (at all Levels), which mainly consist of "Functional Skills" at Level 2 corresponding to good attainment by end of secondary schooling, or below (i.e. Entry level, Level 1). Rather than specific to occupations however, Functional Skills – previously known as Skills for Life – are rather focusing on digital inclusion than on labour productivity and improvement in earnings.

Based on data collected by Eurofound, Gonzalez Vazquez, et al. (2019) provides evidence on the growth of IT skills within job roles in recent years and how digital and social skills coincide in occupations, but the data is not informative to quantify digital skills, which specific skills are involved and how it might impact on earnings. The evidence presented in this study primarily extrapolates qualitative evidence. Similar, the major study commissioned by the Department for Culture, Media and Sports (DCMS) on digital skills for the UK economy by ECORYS (2016) was primarily based on desk research, stakeholder interviews and employer case studies. While this study points towards some key issues like the shortage of some skills affecting growth and business investment, it does not offer a systematic analysis of the type of digital skills required and therefore, only draws out some general policy conclusions on enhancing skills and more coordinated action amongst stakeholders. Internationally, the book by Wuttke, Seifried and Niegemann (2020) presents similar work on the integration of digital skills in education programmes aiming at mid-level skills. Again, most of the work is based on qualitative case studies providing insight in the use of innovative mechanisms of education of digital skills or skills as such, but not resulting from a systematic analysis of empirical data from jobs about digital skills and related qualifications.

For the UK, the only comprehensive empirical analysis on the level and type of digital skills involved in mid-range skills jobs we know of was produced by Burning Glass Technologies (2019) based on online job adverts. Key findings here point towards digital skills as a near-universal requirement, for example skills like Microsoft Office and other productivity software tools across all skills levels. This study also exhibits significant wage differentials of digital skill of about 29% - similar to the figure in Falck et al. (2022) and increasing across the skills spectrum.

Internationally, Kiener et al. (2019) delivered a high-quality empirical study on the extent to which mid-skills jobs involve digital skills based on Swiss occupational training curricula for apprenticeships. Similar to the analysis carried out below, this study obtains key structural variables on the nature and extent to which digital skills are used from processing documents with text analysis methods. The central finding of the study is the overall positive effects of IT skills on wages. Similar to what is being investigated below for English apprenticeships further below, different types of IT skills are found to be associated with different labour market returns and "General digital skills (ICT &

[6] Digital skills: Challenges and opportunities | CEDEFOP (europa.eu)

application) have higher labour market returns in terms of wages than technology-specific types of IT skills (CNC & CAD skills, handling system technologies, handling control technologies).

Policy action around enhancing digital skills

In recent years, a range of policy initiatives started embedding digital skills in general and vocational education, both in the UK and internationally. At the Level of the EU, the European Training Foundation in Turin – an EU agency supporting EU Member States to reform education, training and skills – carries out a range of programmes to raise awareness for common frameworks like EU Digital Competence Framework to become more widely used across education providers. The focus of such initiatives is to offer tools for schools and colleges for the assessment of their education provision in terms of covering digital skills and to launch pilot projects enhancing them in education settings across the piece, i.e. not limited or targeting explicitly the mid-range skills or vocational education.[7] Similar assessment tools have been developed for commercial sectors, such as Pro Edge from PwC, and are used widely internationally by mainly large companies.

In the UK, the "UK Digital Strategy" laid out a government road map on enhancing digital skills Department for Digital, Culture, Media & Sport (2017). It created (local) Digital Skills Partnerships (DSP) of public, private and third sector organisations to facilitate the development of (local) digital skills programmes, enhance digital inclusion and support businesses to upskill their staff (Department for Digital, Culture, Media & Sport 2018). A key element of the strategy are "Skills Bootcamps", essentially free (mostly online) courses of up to 16 weeks on specific skills relevant to local employment opportunities. Individuals can access such education free of charge and are being offered an interview with a local employer on completion, while businesses accessing the service are requested to contribute to the costs (less so for small and medium-size firms). Across other OECD countries, similar strategies emerged, including the German "Education Initiative for the Digital Knowledge Economy" (Bundesministerium für Bildung und Forschung, 2016). As in the UK, the purpose of these schemes is not really operational, but to create a wider framework of stakeholders to coordinate activity.

Although policy actions in the UK and elsewhere are significant and involve considerable investment by governments, the evidence-base on the impact of such interventions is less rigorous than the bold policy action suggests. Largely supported by survey data like the Employer Skills Survey in the UK, there are strong indications that the shortage of digital skills creates problems for employers to achieve planned staffing and capacity targets (38% of all businesses affected by skills shortages, see Winterbotham et al., 2020). However, the surveys don't normally offer a way to quantify the impact of the shortage on hard outcomes like productivity or turnover or how they compare to other factors like local skills availability changing more generally due to demographic change. Therefore, impact assessments largely consist of upfront appraisals rather than rigorous cost-benefit analyses investment return measures when investing in digital skills from such data.

While the Employer Skills Survey produces some further insight – for example whether basic or advanced digital skills are creating the reported skills shortages – more granular detail on the specifics of digital skills cannot be obtained (Winterbotham et al., 2020). Similar data – using employer surveys – underpins the strategies in Germany and elsewhere. For mid-range skills jobs, there is some evidence based on German data on details of the digital skills involved, indicating relevance of software development in specialist digital roles and management and quality aspects in commercially-focusing roles, while database development and IT security are pivotal in both

[7] European Training Foundation (undated), see [Digital skills & learning | ETF]

(Conein, et al. 2017). In addition, there are surveys across the IT sector on shortages of specific skills like the Spinks survey (Harvey Nash Group, 2021), which point towards specific shortages on specialist skills in cyber security, big data/analysis and technical architecture.

Summary

As a summary, we find that the empirical evidence on how much digital skills are involved in apprenticeships and related occupations at mid-range skills is quite limited, suffering both from the lack of a consistent definition and measure such skills and a lack of empirical data available. In any case, different levels (basic and advanced) and different nature of digital skills involved (generic and expert) are likely to impact differentially on earnings differentials. This will be subject to empirical tests in the following.

4. Construction of the database

Data origin and initial processing

The data used in the following have been taken from four main sources

1) **Apprenticeship vacancy data**. Originally, we web scraped vacancies on a daily basis from the findapprenticeship.service.gov.uk website using Beautiful Soup and other packages in Python. Because every single vacancy is posted on its own website, the HTML format of the adverts already provides a semi-structured data format as we work towards a structured database. In addition, inside the HTMLs, there are a few elements, which follow a standardised description, which corresponds to fully structured data.

   Figure A.7 in the appendix shows an example of an advert: While there are great differences in the description of the job roles in the free text of the advert, in particular about knowledge, skills and behaviour (i.e. unstructured text data), some fields in the advert also provide structured information, such as working hours per week, pay, duration, the relevant Apprenticeship standard, starting date and work location, which can be stored as structured data and merged to further databases. These fields were transformed into quantitative research data for the whole set of apprenticeship vacancies (433,799) based on the 303,028 adverts and further processes, e.g. by removal of errors and by processing structured information, which had not been consistent, into comparable data, in particular to gain variable on hourly pay and type of education provider. For the descriptive analysis, the job ads also then weighted by the number of vacancies included.

   Based on our Freedom of Information Act Request, the data were later provided directly by the Education and Skills Funding Agency (ESFA) in the same structured format and were also made available publicly later combining structured characteristics and descriptions with free text. The unstructured text data of descriptions of duty, skills and desired qualifications were then used to create structured data from the full text, see below. Using the vacancy data, we describe the utilisation of digital skills in apprenticeships and estimate the return to different digital skills.

2) **Apprenticeship Standard data.** Because the adverts included the Apprenticeship Standard title, the database was linked to structural data from a database held in the Institute for Apprenticeships and Technical Education on characteristics of apprenticeship standards, such as the “route” (i.e., the sector), level of education, maximum funding available,

provider, etc.

3) **Geography.** Employer postcodes included in the adverts allowed to link the complete dataset to further geography, including Travel-to-Work Areas (TTWA).

4) **Annual Survey of Hours and Earnings data.** Finally, data available from the Institute for Apprenticeships and Technical Education allowed for an exact match of apprenticeships and SOC-Code. The match allowed us to aggregate some of the data obtained from the adverts to link these to ASHE data at the level of three-digit SOCs. Based on the linked data between ASHE and the vacancy data, we estimate the returns to digital skills at occupation-level.

While descriptions and the empirical framework derived from these data are being carried out for all vacancies, including expiring frameworks, both descriptive and regression analyses only use frameworks with a minimum of 50 apprenticeships across all time points to avoid idiosyncratic errors from small cells. We further restrict data to vacancies following Apprenticeship Standards, thereby removing 31% of all observations of the old "framework" apprenticeships without a link to SOC-Codes (See Table A.1 in the appendix).

Text mining of vacancies and standard documents

The processing steps undertaken in order to create structural data from the free text information, which were implemented using the package tm in R, are as follows:

- Unprocessed information from the description is first moved into a corpus object, which acts like a data frame for text data, i.e. a dataset, where rows represents individual documents. In our case, every job advert is one datapoint and the field "description", which includes the free text under "Apprenticeship summary" about the occupations aimed for with the apprenticeship, is one document inside the corpus.
- We then remove some detail: Generally, we transform data to lower case and further reduce the complexity by stemming the words. Stemming removes the prefixes and suffixes from words and derives the root word form and meaning.
- We remove stop words and unnecessary space as well as any punctuation to create a plaintext document.
- We transform the corpus into a document term matrix, which includes the frequency of terms that occur in each apprenticeship advert (i.e. a row represents one advert and the columns of the matrix represent one term).
- We then summarise frequencies across the document term matrix by specific characteristics of the structured data, such as the Level and the route of the apprenticeship.

The outcome from the processing are frequencies of words, which are subsequently used to create dictionaries to process the number of digital skills in vacancies. Frequencies are often shown in Word Clouds, where the size of the font indicates the relative frequencies of the terms, see Figure 6 for the example of apprenticeships in the "digital" route. As can be seen from the example, some high-frequency terms, such as "apprentice" or "work" are generic and were removed before further using the data to create a dictionary.

A similar analysis was undertaken with the Apprenticeship Standard documents. Here, all 25 Apprenticeship Standard documents of the digital route were used to create a corpus and the same processing was implemented to create an alternative dictionary from these documents using the highest-frequency terms, see below “Analysis based on framework derived from Apprenticeship Standards documents”.

Figure 6. 500 most frequent terms in “digital route” apprenticeships.

Source: https://www.gov.uk/apply-apprenticeship.

The key outcome of the mining is the creation of data dictionaries in order to provide description of occupations by number and type of digital skills involved. In processing the data based on a dictionary, we follow similar work carried out by Stops et al. (2021), which applies key words on hard and soft skills requirements in specific jobs from external data, similar to O*NET. While Stops et al. (2021) augment the catalogue of skills requirements based on additional keywords mined from the text, our dictionary itself is derived from the empirical data of either the vacancies or the standard documents as no available catalogues of digital skills can be applied and the empirical frameworks cover a wider range of digital skills in addition to occupation-specific skills, which are in focus for this study.

We also explored the use of further methods to create structural data from the text, such as the dispersion of words inside the advert and bivariate frequencies of words selecting subgroups of apprenticeships by tokenising the core. However, ultimately available methods for quantitative text analysis remain largely descriptive and the use of keywords seems sufficient.

Similar to Turrell et al. (2019), we processed the data to create a matching of vacancies to the UK’s Standard Occupational Classification (SOC). However, because the semi-structured database allowed us to match all of the regulatory documentation of related apprenticeship standards for each advert, we later decided to use a related look-up table between apprenticeships and SOC-Codes available from the Institute for Apprenticeships.

5. Descriptive analysis of digital skills in apprenticeships

Analysis based on framework derived from vacancy data

Construction of the dictionary

A key objective of this research is to gain a more granular description of digital skills in apprenticeships based on vacancy data as the conventional survey data does not often include detailed information on job tasks and skills involved. However, the analysis of textual data is a daunting task, involving understanding job tasks based on numerous words and phrases with large number of errors, not to mention to correctly understand the meaning behind the phrases.

In this paper, we adapt a data-driven method to understand digital skills in apprenticeships by firstly creating a word sheet containing all words, which appeared in job description and skill requirements. The word sheet is a table of frequencies in the processed text body, which is often shown in an intuitive format as a word cloud[8]. The word sheet used in the following was created based on two fields from the structured data on "job description" and "skills requirement" taken from the adverts using the tm package in R. We identify the relevant digital skills manually by removing general words such as "work", "will", "apprentice", etc. and then perform exact matching with the job adverts to label the digital related jobs.

We are aware of the limitations of using keywords to identify digital jobs. It may contain inaccurate keywords, such as program, store, system, office, and neglect unknown short-hands or specific software for particular use, such as Solidwork. Moreover, as there are numerous words or terms conveying digital related job tasks or skills, it is inevitable to group different keywords with similar meaning into a group to simplify and conceptualise the digital skills used in jobs. This grouping keyword might introduce measurement error and disregard some heterogeneity. Because of these deficiencies, we created an alternative approach to operationalise digital skills (next section) and re-estimate the Mincer models in order to validate key findings.

Table 1 presents the keywords that have been selected and used to identify the digital skills. We categorise them identifying ten clusters of digital skills. The keywords are fundamental to the analysis to understand the incorporation of digital skills in jobs. The percentages of digital skills may vary with the inclusion of different keywords, leading to ambiguous results. However, one of the objectives of this research was to create a data-driven method, which can be both replicated and extended by simply changing the keywords and thereby including further specific skills associated with the ten clusters. These are:

- 'Social media' refers to the utilisation of well-developed software by either mobile devices or computers. It is related to creating and editing digital content and maintaining networks.
- 'Microsoft and office' refers to the use of conventional office software in job tasks, such as word processing, numbers manipulation, etc.
- 'Digital' refers to the skills that have been used in e-commerce and behaviours on the internet.
- 'General software' includes the software used for general purposes to fulfil the basic function in daily life.
- 'Computers' refers to the digital skill relating standard computer manipulation.
- 'Professional software' refers to the professional digital skills involving manipulating relevant software.
- 'Computing' refers to the general computing skills, regardless of the purpose of computing and how to carry out the computing.
- 'Computing language' refers to the popular programming languages.
- 'Data' refers to any job tasks relating to manipulating with data.

[8] See Figure XX in the appendix for an example for selected apprenticeship sectors.

Table 1. Pyramid of skills with keywords.

Digital skills	Keywords
Microsoft and office	'microsoft'; 'word'; 'powerpoint'; 'excel'; 'visio'
Emails	'email'; 'mailbox'
Computers	'computer'; 'desktop'; 'browser'; 'download'; 'ipad'; 'web'; 'laptop'; 'router'; 'windows'
Social media	'blog'; 'facebook'; 'linkedin'; 'amazon'; 'tiktok'; 'youtube'; 'whatsapp'; 'ebay'; 'twitter'
General software	'acrobat'; 'apps'; 'photoshop'; 'software'; 'dropbox'; 'skype'; 'zoom'
Professional software	'autocad'; 'linux'; 'solidworks'; 'amp'; 'aws'; 'cyber'
Computing	'code'; 'programming'
Computing language	'css'; 'xml'; 'json'; 'php'; 'java'; 'python'; 'C'
Digital	'digital'; 'ebooks'; 'ecommerce'; 'online'
Data	'data'; 'database'; 'mysql'; oracle; 'django'

Source: https://www.gov.uk/apply-apprenticeship.

The first empirical difficulty is to understand the level of digital skills. Previous work aiming for quantitative data on digital skills establishes a pyramid containing self-defined concepts and keywords to differ the different levels of complexity, see above Beblavy, et al. (2016). Similarly, we decided to group digital skills into different levels of complexity depending on the level of apprenticeships, where they are most frequently observed (i.e., Intermediate or Advanced Apprenticeships following the categorisation used in the regulation). This data-driven method of classification better reflects the incorporation of digital skills at different levels of proficiency: The increasing Level of Apprenticeships (similar to the Levels of the Qualifications and Credit Framework QCF more widely) represent increasing standards of knowledge, skill and competence required and allows to describe them as "basic" (i.e., focusing on life skills/skills for digital inclusion more widely) and "Advanced" (i.e., occupation-specific skills found in Level 3 vocational education).

Table 2 presents the percentages of apprenticeships containing the digital skills by the levels of apprenticeships. Based on the distribution of levels of apprenticeships for the digital skills, we group the ten digital skills into two groups, basic and advanced digital skills. The basic digital skills are defined as when the digital skill is more frequently used in lower-level of apprenticeships, and vice versa for the advanced digital skills. It is worth noting that there are no digital skills that dominate in Intermediate Apprenticeships compared with Advanced and Higher Apprenticeships. For the six most frequently demanded digital skills in Advanced Apprenticeships compared to Intermediate and Higher Apprenticeships, we label them as the 'basic' digital skill, including utilising Microsoft, computer knowledge, manipulating emails, social media, digital-related skills, and data skills. On the other hand, there are four digital skills belonging to 'advanced' digital skill, according to our classification. The apprenticeship vacancies suggest that Microsoft, computers, and data skills are most wanted skills of employers. More professional skills are relatively less needed but still have a strong demand amongst Higher Apprenticeships.

Table 2. Percentage of digital skills across levels of apprenticeships.

		Levels of apprenticeships			
		Intermediate Apprenticeships	Advanced Apprenticeships	Higher Apprenticeships	Total
Basic	Microsoft and office	7%	23%	12%	15%
	Computers	14%	26%	17%	20%
	Emails	4%	13%	2%	8%
	Social media	1%	4%	2%	2%
	Digital	7%	13%	14%	10%
	Data	7%	21%	25%	14%
Advanced	General software	2%	8%	20%	6%
	Professional software	0%	0%	6%	1%
	Computing	1%	3%	11%	3%
	Computing language	0%	1%	5%	1%

Notes: All table are weighted by the number of vacancies. The percentages are calculated based on the apprenticeships containing at least one digital skill.
Source: https://www.gov.uk/apply-apprenticeship.

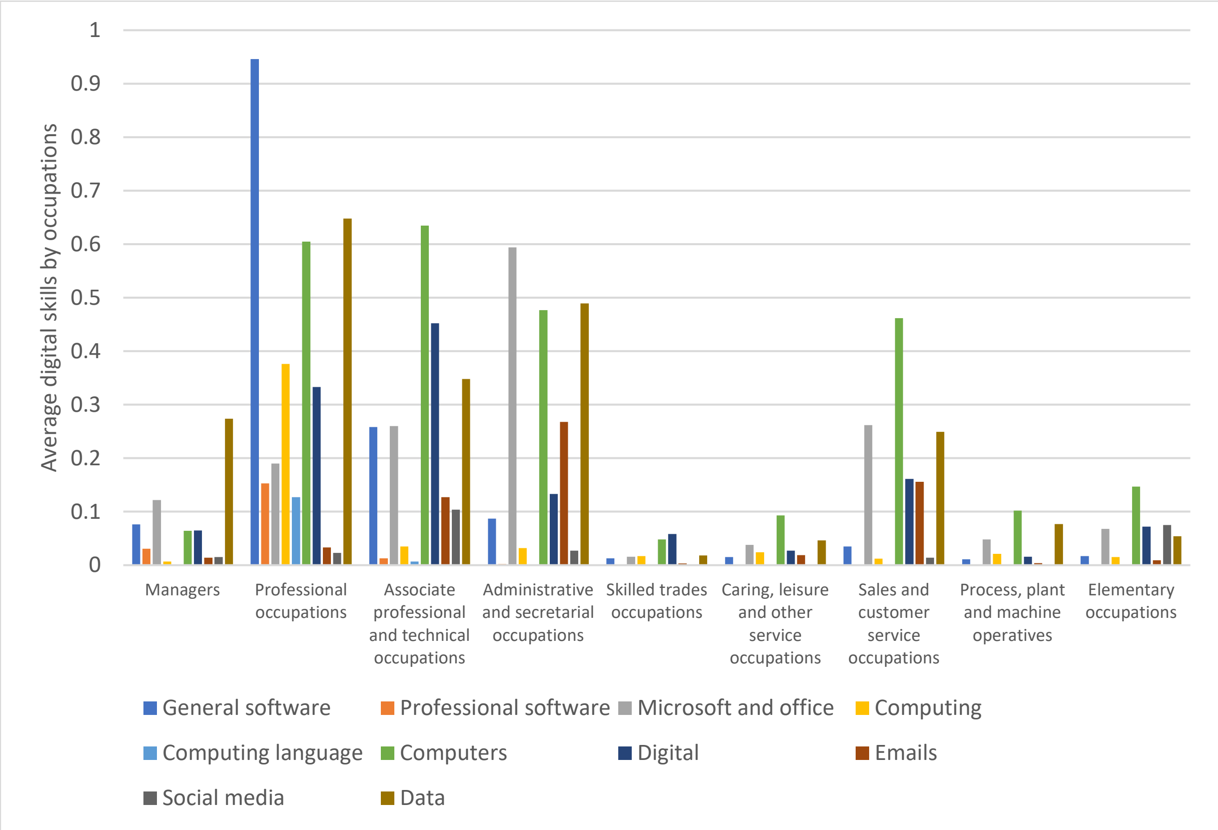
Descriptive analysis

In the subsequent sections, we are limiting the analysis to vacancies related to Apprenticeship Standards, i.e. removing vacancies still following previous regulation, as the Standards were mapped to SOC codes by the Institute for Apprenticeships. We also exclude a few standards, where less than 50 apprenticeships were found in the data to avoid the idiosyncratic results (less than 2% of the total). Figure 7 shows the results of digital skills required across SOC categories, i.e. the average numbers of digital skills demanded for each occupation. We find:

- General software is required in both professional and associate professional occupations, while professional software is only really found in professional occupations, similar to computing languages.
- Amongst the occupations at mid-range skills, Administrative and secretarial occupations require substantial Microsoft skills compared to other occupations. The results also show that administrative occupations have the highest demand for data and computer skills. In the context of ongoing substitute capital for labour in mid-range occupations (Acemoglu and Autor 2010), the administrative jobs have been routinised by the advanced technology. We speculate that some administrative related jobs have adapted the relevant technologies and improve the employability in the labour market, in this case, the data skills.
- For caring, leisure and service occupations, we find some demand for computer skills. We expect that the relevant jobs will need to manipulate computers or tabulate data in order to provide customer services as these technologies have become more widespread across all service occupations.
- Sales and customer service occupations require different types of digital skill, such as digital related skills and data skills. This implies the jobs may have strong diversity in job tasks and different tasks are increasingly requiring more digital skills than other occupations.

- Lastly, we don't find strong requirements for digital skills for managers, except for data skills. This may be because the type of skills required by managers are more conceptual than operational and might not be captured well by our data-driven approach.

Figure 7. Digital skills in major occupational groups.



Source: https://www.gov.uk/apply-apprenticeship.

The results suggest that occupations have evolved to adapt to the rapidly changing environment by embracing different types of digital skills to improve productivity, suggesting the importance of provision of digital skills to job candidates. We believe our results provide evidence on how the occupations that were estimated to be replaced by technologies adapted and incorporated dgitial skills to improve the competitiveness in the labour market. In order to improve productivity, employment, and earnings, required qualifications would need to retain occupational subject knowledge, while enhancing the use of new technologies like ICT by providing digital skills specific to these occupations.

More detailed findings and development since the Covid-19 Pandemic

A more detailed analysis (Appendix Figures A1-A5) describes the data within detailed SOC occupations. We observe two patterns. First, for some occupations, such as trades, sales, and operatives, some jobs require significant higher-level digital skills than other jobs in the same SOC one-digit category, i.e., these jobs have more tasks requiring digital skills, making them genuine digital jobs. On the other hand, for other occupations, the requirement of digital skills follows a linear or quadratic trend within the one-digit major group, suggesting digital skills provide supportive role for those jobs.

Finally, Figure A6 describes the average frequency is of digital skills before and after the Covid-19 Pandemic within SOC groups. If at all, these comparisons show very limited changes in recent years: In professional and associate professional/technical occupations, we observe lower frequencies of digital skills in recent months across most areas, except computer skills. In the more intermediate-level administrative and secretarial jobs, we find small increases in the use of digital skills. On average, the frequency of computer skills increased from 0.43 to 0.51, and a similar increase in Microsoft and office. Some growth in digital and computer skills also affected sales and customer service occupations, which entail fewer digital skills on average. Changes are small generally, but computer skills are mentioned more across all occupation groups.

One interesting finding – the reduction of "data" and "general software" in professional and associate professional jobs – might suggest that these roles are changing in the presence of more widely available cloud solutions from large technology companies, requiring fewer specialist roles in the firms/less software knowledge than before. While this trend has been observed for some time, the Pandemic and increased working from home probably accelerated it. Similarly, the small positive change across most digital skills in administrative and secretarial jobs could also to an extent result from changing work practices after the Pandemic.

Clustering occupations by digital skills involved

To group apprenticeship vacancies into clusters containing similar level of digital skills, we employ K-Means clustering. We specify the algorithm to create four empirical clusters making use of the frequencies of digital skills along the ten dimensions, which bring four groups with relatively similar use of specific digital skills.

The algorithm automatically classifies entries into groups based on the Euclidean distance without labelling beforehand. Based on the digital skills defined in the previous sections, we group the apprenticeship vacancies into four groups. To reflect the use of digital skills we identify the numbers of the appearance of digital-related keywords and believe that the frequencies may reflect both the usage and the intensity of digital skills in job tasks. The results are shown in Table 3 below:

- Panel A shows that the second cluster contains fewer digital skills, while other clusters contain at least one digital skill, suggesting all "non-digital" apprenticeships are grouped into the second cluster only.
- Panel B shows the breakdown between clusters and levels of apprenticeships. For the clusters containing digital skills, we find that the first cluster contains more higher apprenticeships compared to the third and the fourth clusters.
- Panel C presents the detailed incorporation of digital skills across clusters. The second cluster contains fewer digital skills compared with the other three clusters. All apprenticeships in the first cluster requires data skills and also requires more Microsoft and computer skills.

The third cluster is centred around Computer skills and General Software, Microsoft, Digital, Email and Data skills. Lastly, all apprenticeships in the fourth cluster require Microsoft skills and among these apprenticeships, Computer, Email, and Data skills are mostly demanded. This panel sheds light on how apprenticeships are clustered and the skills around which are centred.

Table 3. Cluster analysis.

Panel A. Percentages of apprenticeships with at least one digital skills in each Cluster

Cluster	Intermediate apprenticeships	Advanced apprenticeships	Higher apprenticeships
1	100%	100%	100%
2	20%	36%	34%
3	100%	100%	100%
4	100%	100%	100%
Total	30%	54%	48%

Panel B. Clusters and levels of apprenticeships

Cluster	Intermediate apprenticeships	Advanced apprenticeships	Higher apprenticeships	Total
1	20.86	64.25	14.89	100%
2	50.53	43.26	6.21	100%
3	18.58	74.5	6.92	100%
4	19.27	75.25	5.48	100%
All	43.23	49.56	7.21	100%

Panel C. Clusters and detailed digital skills

Clusters	General software	Professional software	Microsoft and office	Computing	Computing language
1	13.60%	2.70%	23.70%	6.90%	1.50%
2	4.10%	0.40%	7.30%	2.00%	0.60%
3	29.30%	2.10%	28.20%	7.60%	3.10%
4	15.80%	1.20%	100.00%	3.30%	1.20%
Total	7.70%	0.80%	15.20%	3.00%	0.90%

Clusters	Computers	Digital	Emails	Social media	Data
1	30.00%	11.90%	14.00%	2.20%	100.00%
2	11.00%	6.60%	5.10%	1.30%	0.00%
3	96.40%	39.40%	25.60%	13.50%	26.40%
4	38.10%	13.50%	28.20%	2.70%	34.30%
Total	21.00%	10.10%	8.80%	2.40%	15.00%

Source: https://www.gov.uk/apply-apprenticeship.

Table 4 below presents the ten most demanded apprenticeships in each cluster. Within the second cluster, we observe a wide range of occupations, as well as a large residual. In the first cluster, the occupations are more 'digital-focused', in which business administrator accounts for around 33% of all vacancies in this cluster. In the third cluster, we observe more digital marketer and the 10 most demanded occupations account for almost 83% of all vacancies. In the fourth cluster, business administrator accounts for 44% vacancies. We also observe more customer related occupations, such as customer service and customer specialist. There are more medium skilled jobs included.

Given the results, it appears that digital technology has been introduced more widely into medium-level jobs rather than jobs that require intensive people skills.[9]

Table 4. 10 most frequent occupations in empirical clusters.

Cluster 1			Cluster 2		
Business administrator	6.16	32.78%	Business administrator	5.90	9.65%
Customer service practitioner	5.72	12.87%	Hospitality team member	5.43	8.02%
Engineering technician	11.44	3.54%	Customer service practitioner	5.55	7.68%
Data analyst	11.56	3.25%	Hair professional	4.16	4.77%
Digital and technology solutions professional (integrated degree)	9.83	3.25%	Engineering technician	7.05	4.66%
Assistant accountant	7.82	2.93%	Production chef	5.57	3.66%
Infrastructure technician	8.21	2.83%	Supply chain warehouse operative	6.19	2.99%
Teaching assistant	4.65	2.48%	Early years educator	4.68	2.95%
Digital marketer	10.66	2.30%	Adult care worker	6.31	2.92%
Recruitment resourcer	8.72	2.03%	Commis chef	6.00	2.71%
Residual		30.01%	Residual		47.55%

Cluster 3			Cluster 4		
Digital marketer	6.57	22.77%	Business administrator	6.45	44.41%
Business administrator	5.47	16.73%	Customer service practitioner	5.20	14.58%
Infrastructure technician	7.51	15.70%	Assistant accountant	7.18	7.02%
Customer service practitioner	5.33	12.38%	Infrastructure technician	6.19	5.22%
Junior content producer	7.98	3.22%	Digital marketer	6.87	3.18%
Software development technician	5.43	2.59%	HR support	10.15	1.83%
Public service operational delivery officer	10.85	2.49%	Customer service specialist	5.53	1.76%
Software developer	9.75	2.39%	Paralegal	8.06	1.74%
IT solutions technician	7.90	1.59%	Recruitment resourcer	5.04	1.18%
Pharmacy services assistant	4.30	1.41%	Engineering technician	6.07	1.08%
Residual		17.45%	Residual		17.05%

Source: https://www.gov.uk/apply-apprenticeship.

Analysis based on framework derived from Apprenticeship Standards documents

Construction of the dictionary

In a second approach of deriving an empirical framework, we used the official "Apprenticeship Standard" documents published by the Institute for Apprenticeships. We focus on Standard documents for occupations in the "digital" sector, which refers to 26 standards at advanced and higher levels (out of the currently 638 standards). The corpus used to create this alternative

[9] This is consistent with findings in the extensive literature on the impact of automation on job market (Autor et al 2003; Acemoglu and Autor 2011) of which technologies have broadened the boundaries of medium-level jobs.

dictionary makes use of the full text as found on the website summarising the "Details of standard". We create the dictionary resulting from word frequencies within these documents, which is then applied to evaluate the extent to which such skills are being employed in apprenticeships across all sectors.

To obtain the dictionary, we process the standard documents by creating individual text bodies for all the standards related to apprenticeships at a particular level. Hence, we are merging all at various Levels 3, 4-5, 6 and 7 to one corpus at each level. Within these four larger text corpora, we remove stop words and high-frequency generic terms after stemming the words, for example removing "apprentice", "servic" and "standard".

The resulting word frequencies then establish an alternative data dictionary extracted from the processed text body, which is based on a minimum threshold of words included in the documents. We select terms, which in the combined documents come up at least fifty times, for our dictionary. As can be expected, these terms are much more generic than digital skills derived from vacancies as – rather than specific skills or software involved – this dictionary more clearly focuses on the job tasks involved with using digital technology, such as "Analysis" or "Programming", see Table 5 below.

Table 5. Most frequent words* in Standard documents.

Level 3	Level 4-5	Level 6	Level 7
access	access	appli	appli
assess	analysi	creativ	data
data	analyst	data	design
digit	appli	design	duti
inform	applic	digit	engin
instal	cyber	network	game
network	data	secur	Network
secur	design	softwar	organi
softwar	digit	solut	platform
system	identifi	specialist	process
technolog	inform	system	program
	network	techniqu	programm
	process	technolog	requir
	secur	test	research
	softwar		scienc
	solut		softwar
	techniqu		solut
	test		system
	tool		technolog
	user		tool

* Frequency of at least 50 within combined text body from apprenticeship standards at different levels after removing stop words and generics.
Source: Institute for Apprenticeships and Technical Education (download 11/11/2021)

As the table suggests, the standard documents show considerable overlap in some of the skills and tasks within digital apprenticeships. For example, "software", "data" and "digit" describe relevant skills and tasks at all levels of apprenticeships within the digital route, whereas "game", "specialist" and “program” only appear in higher-level apprenticeships. This description provides some evidence that many skills/tasks of Level 3 apprenticeships are also relevant to digital apprenticeships at higher levels.

In contrast, there are some specific digital-related tasks, which are unique to higher-level digital apprenticeships. As higher-level apprenticeships show very similar terms with the 50 most frequent words, we consolidate the four different dictionaries into two, one at “advanced” and one at “higher” levels, corresponding to Level 4-7 and Level 3 apprenticeships – there are no apprenticeships standards within the digital route at Level 2.

The resulting dictionary is shown in Table 6 below. It provides a dictionary relevant to advanced apprenticeships and higher apprenticeships, which we then apply across all apprenticeship standards at Levels 3 and above in the subsequent analysis to describe how much apprenticeships across the economy incorporate the tasks and skills associated with apprenticeships in the digital sector.

Table 6. Dictionary derived from standards data.

Advanced	Higher	
access	analysi	platform
assess	analyst	process
data	appli	program
digit	applic	requir
inform	creativ	research
instal	cyber	scienc
network	design	solut
secur	duti	specialist
softwar	engin	techniqu
system	game	test
technolog	identifi	tool
	organi	user

Source: Standard documents from the Institute for Apprenticeships

Applying the dictionary to the standard data

Applying the dictionary to analyse word frequencies in individual standard documents, Table 7 shows the average frequency of the words found in individual standards by routes. This description clearly shows that digital apprenticeships have the highest frequencies across all levels, but at the same time, we find an increase in digital skills as we move across the levels of qualifications, i.e. there are relatively more digital skills found at higher levels generally, including in sectors where digital skills are not as widely used, such as agriculture and care services.

In addition, the data show that apprenticeships in some sectors incorporate a large amount of digital skills, for example in engineering and education, suggesting that a significant range of activities involve the use of digital skills, specifically at higher levels of skills in these sectors. The extent to which such skills are being used at higher levels compared to lower-levels – for example in education and health and science – suggests that a range of activities involve the use of software, digital skills and related tasks, such as analysis and evaluation of data and the use of specialist platforms.

Table 7. Average frequency of terms included in individual standard documents, by route.

	Level 3	Level 4-5	Level 6	Level 7
Agriculture, environmental, animal care	17.5	37.2	39.5	41.5
Business and administration	22.6	37.9	18.7	68.7
Care services	16.0	20.0	12.5	26.0
Catering and hospitality	10.0	20.0		
Construction	21.3	30.9	28.7	64.7
Creative and design	15.1	41.2	35.0	51.7
Digital	62.3	93.8	126.8	267.3
Education and childcare	16.8	11.0	12.0	74.0
Engineering and manufacturing	15.8	49.2	34.6	83.5
Hair and beauty	14.0			
Health and science	20.1	23.1	17.5	61.4
Legal, finance and accounting	11.5	20.0	12.1	42.8
Protective services	19.5	32.5	13.3	
Sales, marketing and procurement	16.0	30.6	19.0	
Transport and logistics	15.9	17.2	34.2	
Average	19.1	38.9	30.2	73.3

Source: Standard documents from the Institute for Apprenticeships

6. Association between digital skills and earnings found in regression models

Analysis of apprenticeship vacancy data

Empirical model

Estimates of the life-course earnings returns of digital subject to an analysis of ASHE data further below. In this section, we use the available earnings information from the job adverts for the analysis of the wage differentials associated with specific digital skills in the jobs related to the apprenticeship. To do this, we are regressing earnings on individual digital skills observed in the adverts subject to a fixed effect for the specific apprenticeship standard. The model looks as follows:

$$ln\, w_{ij} = \alpha + \beta DS_i + \gamma Level_i + \delta FE_j + \varepsilon_{ij}$$

Where $\ln w_{ij}$ denotes the log of hourly pay of vacancy i in three-digit occupation k. DS_i and $Level_i$ denote the number of digital skill and level of the vacancy i, respectively. FE_j denotes the fixed effect of three-digit occupation. As we observe strong variation of the incorporation of digital skills within each three-digit SOC occupation, we make use of this variation to estimate whether jobs having more digital skills have higher returns on average.

This research utilises all apprenticeship vacancies listed on the government's website between August 2018 and October 2021. We have used original ONS mapping table to match SOC titles with job titles of vacancies, excluding apprenticeships following the old "framework" regulation (i.e. before the standards) as these cannot be matched to SOC codes. As before, we are excluding standards with fewer than 50 apprenticeships to avoid the idiosyncratic results when examining digital skills. The excluded sample accounts for less than 1% of all apprenticeships operating based on Standards.

Findings based on the digital skills framework derived from vacancy data

Table 8 shows that the effects of digital skills are positive on hourly pay in lower-level occupations compared to the effects in higher-level occupations, especially among administrative, skilled trades, and elementary jobs. Based on the previous results in which we know administrative jobs and skilled trades have incorporated more digital skills than other categories. We expect the results suggest the jobs with more digital skills may have higher productivity and wages although we are cautious about the endogeneity of incorporating digital skills. One of our research interests lies in estimating the effect of digital skills on lower-level jobs that traditionally do not require substantial ICT skills. The results suggest that conventional jobs that do not require strong ICT skills are incorporating more digital skills and the wage premium has been found.

Table 8. Effect of digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of digital skills	-0.036	-0.011	-0.026	0.006**	0.062**
	(0.02)	(0.01)	(0.02)	(0.00)	(0.02)
N	1,622	12,496	43,828	42,685	54,020
	Service occupation	Sales	Operatives	Elementary	
Numbers of digital skills	0.030*	0.007	0.035	0.006**	
	(0.01)	(0.00)	(0.07)	(0.00)	
N	2,7013	32,397	5,787	6,434	

Note: All regressions have included three-digit SOC identifiers and level of apprenticeships as control variables. The standard errors are clustered at three-digit SOC identifiers level.

Source: https://www.gov.uk/apply-apprenticeship.

When categorising digital skills in basic and advanced, see Table 2 above, findings suggest that advanced digital skills have positive impacts on associate professional, administrative jobs and skilled trades (Table 9). The effects are strongest for vacancies trades for skilled trade apprenticeships. In contrast, basic digital skills are associated with lower wages.

Jobs at managerial and professional level do not show any significant coefficient, pointing towards endogeneity of the incorporation of digital skills. For the elementary jobs, we find positive effects for both groups; however, only very few elementary jobs are actually combined with apprenticeships (see Figure A5 in the Appendix), and this category is dominated by warehouse workers and delivery operatives, which are not dissimilar to administrative occupations with formally higher skill levels.

Table 9. Effect of basic and advanced digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of lower digital skills	-0.050	-0.028	-0.073***	-0.017**	0.009
	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)
Numbers of higher digital skills	-0.013	0.003	0.032***	0.028***	0.098***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
N	1622	12496	43828	42685	54020
	Service occupation	Sales	Operatives	Elementary	
Numbers of lower digital skills	-0.005	-0.014	0.012	0.045**	
	(0.05)	(0.01)	(0.10)	(0.00)	
Numbers of higher digital skills	0.077	0.019*	0.051	-0.039**	
	(0.04)	(0.01)	(0.04)	(0.00)	
N	27013	32397	5787	6434	

Note: See Table 3.
Source: https://www.gov.uk/apply-apprenticeship.

Table 10 shows the impacts of digital skills by levels of apprenticeships. For advanced skills, it only has positive impacts on intermediate and advanced apprenticeships. The coefficient is larger for the lower-level intermediate apprenticeships as would be expected from the results by SOC major groups, just above.

As found before for Associate Professional and administrative occupations, we find negative and significant coefficient estimates for lower-level digital skills. In our view, this finding suggest that basic level skills can be to some extent expected. An explicit mentioning of specific basic digital skills (like the use of Microsoft office, email and social media) in job ads likely corresponds to lower-level job tasks and related skills demand.

The interpretation here is that such skills are expected anyway, so the explicit focus of education policy should shift towards support of rather higher-level skills than fundamental training (like the European Computer Driving License), which are essential for digital inclusion, but less so to increase workplace productivity and earnings.

Table 10. Effect of basic and advanced digital skills on wages by levels of apprenticeships.

	(1) All	(2) Intermediate	(3) Advanced	(4) Higher
Numbers of lower digital skills	-0.026**	-0.032***	-0.028	-0.037**
	(0.01)	(0.01)	(0.02)	(0.01)
Numbers of higher digital skills	0.029***	0.053***	0.024***	0.004
	(0.01)	(0.02)	(0.01)	(0.01)
N	226282	106671	104557	15054

Note: See Table 3.
Source: https://www.gov.uk/apply-apprenticeship.

Table 11 shows the impacts of digital skills on apprenticeships that only contain basic or advanced digital skills (the zero category is in both cases no digital skills). In line with the result from above, we only find positive impacts of advanced skills in intermediate apprenticeships. Excluding the advanced skills from the specification yields insignificant coefficient estimates of lower-level digital skills, suggesting there is no difference compared to jobs not including any of them.

Table 11. Heterogeneous effect of basic and advanced digital skills on wages by levels of apprenticeships.

	(1)	(2)	(3)	(4)	(5)	(6)
	Intermediate		Advanced		Higher	
	Basic	Advanced	Basic	Advanced	Basic	Advanced
Numbers of lower digital skills	-0.011		-0.022		-0.043	
	(0.01)		(0.04)		(0.04)	
Numbers of higher digital skills		0.086***		0.022		-0.026
		(0.02)		(0.02)		(0.03)
N	86139	85653	56285	58294	7551	10944

Note: See Table 3.
Source: https://www.gov.uk/apply-apprenticeship.

Table 12 examines the role of digital skills between STEM and Non-STEM occupations. For Non-STEM occupations, the impacts of advanced digital skills are only positive in intermediate apprenticeships and keep decreasing with the levels of apprenticeships. For STEM occupations, advanced digital skills only have positive impacts in advanced apprenticeships.

Table 12. Heterogeneous effect of basic and advanced digital skills on wages by levels of apprenticeships between STEM and Non-STEM occupations.

	(1)	(2)	(3)	(4)	(5)	(6)
	Intermediate		Advanced		Higher	
	Non-STEM	STEM	Non-STEM	STEM	Non-STEM	STEM
Numbers of lower digital skills	-0.033***	0.080	-0.026	-0.033*	-0.030	-0.034
	(0.01)	(0.06)	(0.02)	(0.02)	(0.04)	(0.02)
Numbers of higher digital skills	0.056***	-0.024	0.020*	0.045***	-0.022	0.007*
	(0.02)	(0.03)	(0.01)	(0.01)	(0.05)	(0.00)
N	102814	3857	79310	25247	7430	7624

Note: The definition of STEM occupations follows Grinis (2019).
Source: https://www.gov.uk/apply-apprenticeship.

In summary, the results show that the incorporation of digital skills is endogenous. Basic digital skills are nowadays in many jobs and highlighting the digital skills may imply the jobs require lower-levels of skills. In fact, stating these explicitly in vacancy descriptions seems to be associated with jobs roles. Only advanced digital skills have positive impacts on earnings, and this is restricted to apprenticeships of lower-level.

Coefficient sizes are smaller at the higher-levels of apprenticeships, suggesting that higher-levels of apprenticeships have rapidly adapted digital skills and make them essential and not unique. Overall, the results have one important implication. The incorporation of digital skills is more pervasive than we expected before. Now every job requires some degree of digital skills, implying that the probability of having a job decreases without mastering some digital skills, especially for older workers.

Findings based on job tasks related to digital skills

In an alternative set of results based on a dictionary obtained by text mining the apprenticeship standard documents of the digital sector, we identified job tasks related to working with digital technology from the standard documents of Level 3-7 apprenticeships of the "Digital" route, see Table 5 above. The resulting dictionary consists of relatively higher as opposed to basic digital-related job tasks, see Table 6 above. While the higher tasks include creative design and programming activities as well as specialist techniques, the more basic job tasks are procedural and operational, for example accessing data and using applications in work processes.

Table 13 shows the impact of digital-related job tasks on earnings across occupations. Differences between Table 13 and Table 8 before result from the fact that digital skills are not perfectly associated with digital-related job tasks. To analyse the actual impact of digital skills on job tasks and its association with earnings, we perform the Mincer equation using this alternative dictionary.

As before, digital-related tasks are not associated with higher earnings in each occupation: We find a 0.5% increase in earnings per digital skill added to an advert for professional occupations. Unlike the previous tables, these results suggest positive earnings effects of digital skills across a wider spectrum of occupations, consistent with the findings from above. The association of earnings with digital skills is higher in the mid-range skills occupations, e.g. three times higher in administrative compared to professional roles and twice as high in sales. This is consistent with the findings presented above that administrative occupations show the highest earnings impact.

Table 13. Effect of digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of digital skills	0.012	0.005***	0.008	0.016***	0.004
	(0.02)	(0.00)	(0.01)	(0.00)	(0.00)
N	1622	12433	38347	42099	13683
	Service occupation	Sales	Operatives		
Numbers of digital skills	0.013	0.094*	0.027*		
	(0.01)	(0.01)	(0.01)		
N	7759	3124	544		

Note: All regressions have included three-digit SOC identifiers and level of apprenticeships as control variables. The standard errors are clustered at three-digit SOC identifiers level.
Source: https://www.gov.uk/apply-apprenticeship.

In Table 14, we provide more insight into the nature of the digital skills and their relative earnings effects based on the second dictionary. Here we find higher earnings more often associated with the number of higher digital skills mentioned. In column 4, we find that administrative roles show positive earnings differential of 0.7% per number of low digital skills compared to 3.7% resulting from higher digital skills. The breakdown in other occupations shows significant estimates for sales occupations, which show 3.2% increased wages per number of lower digital skills is included in the advert compared to 14.8% per cent for any of the higher skills. For operatives, we find 6.9% increased wages for lower digital skills, compared with a negative association found for the higher-level skills.

Table 14. Effect of basic and advanced digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of lower digital skills	0.020	0.006***	0.010	0.007**	0.002
	(0.03)	(0.00)	(0.01)	(0.00)	(0.00)
Numbers of higher digital skills	0.008	0.003**	0.005	0.037***	0.006
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
N	1622	12433	38347	42099	13683
	Service occupation	Sales	Operatives		
Numbers of lower digital skills	0.017	0.032	0.069**		
	(0.02)	(0.02)	(0.02)		
Numbers of higher digital skills	0.007	0.148	-0.034***		
	(0.01)	(0.04)	(0.01)		
N	7759	3124	544		

Note: See Table 13.
Source: https://www.gov.uk/apply-apprenticeship.

In Table 15, we show results separately for different levels of apprenticeships with a higher earnings differential associated with the higher-level digital skills for advanced apprenticeships and low or insignificant estimated for higher apprenticeships involving tertiary education. We find discrepancies between levels of apprenticeships. Among higher apprenticeships, only lower digital job tasks are associated with higher earnings, suggesting the endogeneity of incorporating different levels of digital job tasks across levels of jobs.

Table 15. Effect of basic and advanced digital skills on wages by levels of apprenticeships.

	(1) All	(3) Advanced	(4) Higher
Numbers of lower digital skills	0.008	0.008	0.005***
	(0.01)	(0.01)	(0.00)
Numbers of higher digital skills	0.013**	0.018*	0.004
	(0.01)	(0.01)	(0.00)
N	119611	104557	15054

Note: See Table 13.
Source: https://www.gov.uk/apply-apprenticeship.

To mitigate the endogeneity, we estimate earnings differential only if they contain basic or advanced digital skills (the zero category is in both cases no digital skills), similar to what we do in Table 11. After removing the higher apprenticeships requiring lower level of digital job tasks, we find significant positive impact of higher digital skills at 10% level of significance, shown in Table 16.

Table 16. Heterogeneous effect of basic and advanced digital skills on wages by levels of apprenticeships.

	(1)	(2)	(3)	(4)
	Advanced		Higher	
	Basic	Advanced	Basic	Advanced
Numbers of lower digital skills	0.011	-	0.004	-
	(0.01)	-	(0.02)	-
Numbers of higher digital skills	-	0.019	-	0.011*
	-	(0.01)	-	(0.01)
N	64551	54698	6217	6672

Note: See Table 13.
Source: https://www.gov.uk/apply-apprenticeship.

Using Annual Survey of Hours and Earnings data to understand life-type wage differentials

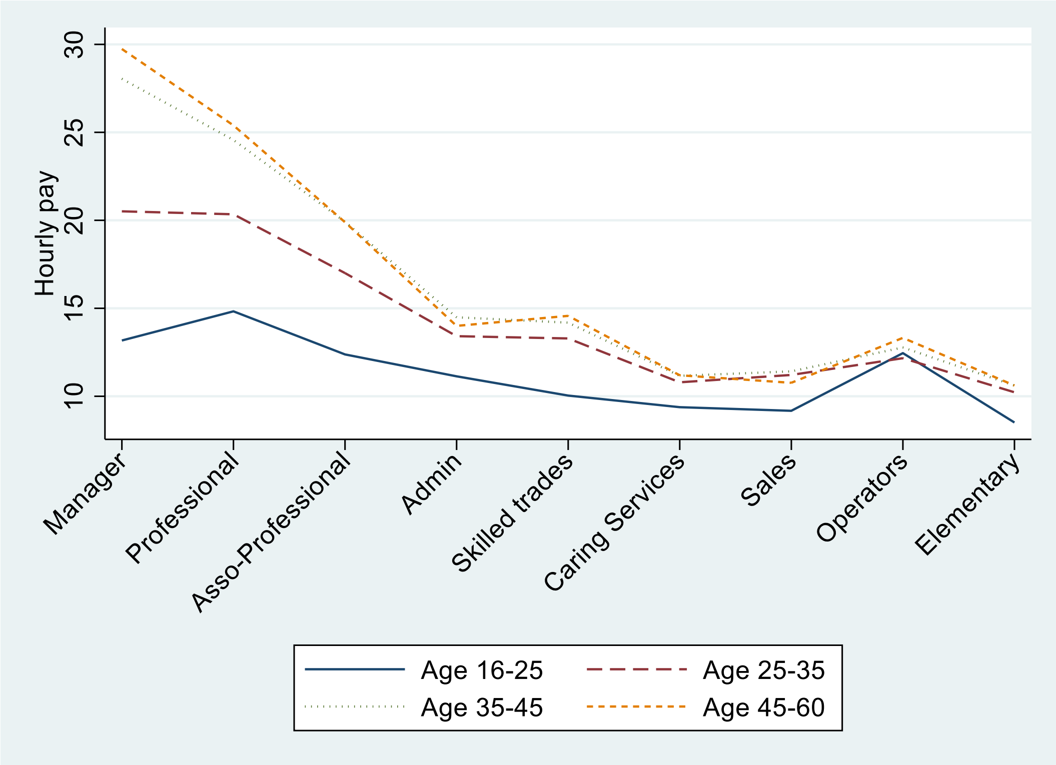
Data descriptions

To mitigate measurement errors of earnings from the vacancy data and measure the impacts of digital skills in the longer term, we use data from the of Annual Survey of Hours and Earnings (ASHE) to extract the information on earnings, which we merge with the vacancy data at local authority and occupation level. The objective of this analysis is to extend from the static wage information included in the vacancy data and to make use of the micro-data for occupations in ASHE, which are collected along with other characteristics, such as age, work experience and other control variables, which can offer to estimate life-course earnings differentials associated with digital skills by mapping occupations to apprenticeship standards. This makes the implicit assumption that apprentices remain in relevant occupations as their work experience increases. Thus, by estimating the earnings differentials in the representative ASHE data, which cover occupational earnings across the age range 16-65, and conditioning on further relevant controls, we aim to understand the medium and long-run relationship between digital skills in jobs with mid-range qualification and related earnings.

We use ASHE data from years 2020 and 2021 and extract individual-level data for earnings. To merge ASHE data with vacancy data, we collapsed vacancy data into cells based at three-digit level of the Standard Occupational Classification (SOC) and Travel-to-Work areas and then merge the information on digital skills included in these cells at occupation-region level to ASHE. This results in a high-quality dataset, where 95% of the cells from the vacancy data have been matched to ASHE.

Using ASHE data, Figure 8 shows career development across occupation groups. In the 16-25 age group, the differences between occupations are relatively small. The higher socio-economic occupations, such as managers and professionals, have deep slope of earning growth.

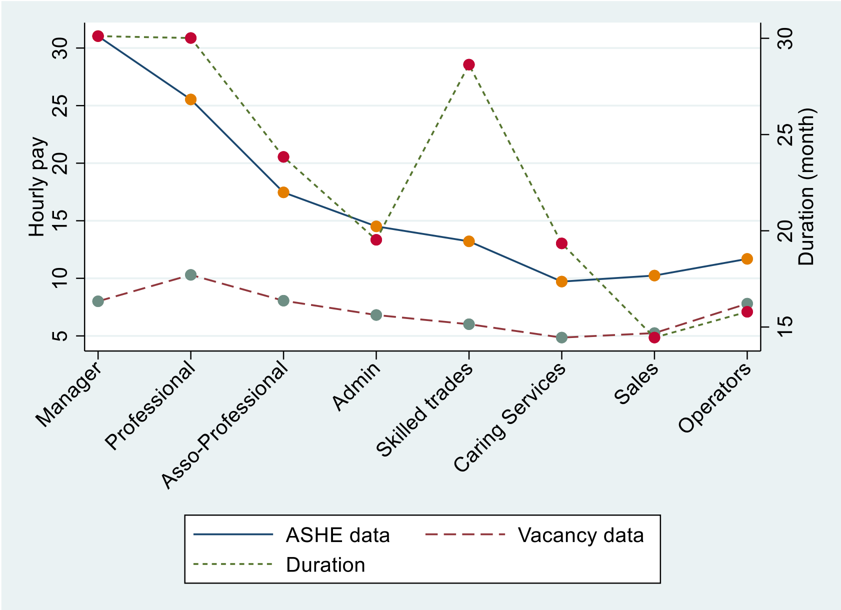
Figure 8. Distribution of occupations by age groups using ASHE data.



Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

After matching with ASHE data, we compare the earnings information across the two datasets. We find a similar pattern between data from two sources across occupations. However, the earnings of apprenticeships are much lower than the earnings from ASHE data as ASHE data contains more ordinary jobs, shown in Figure 9. The gaps are larger in managers and professional occupations, compared to the gaps in caring services, and operators, although the differences in earnings are quite smaller during apprenticeships.

Figure 9. Differences in earnings and training duration between apprenticeships and ASHE occupations.



Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

Empirical estimates

To approximate life-time earnings differentials from digital skills in occupations with mid-range qualifications, we estimate the following linear regression model:

$$ln\, w_{ikr} = \alpha + \beta DS_{kr} + \gamma X_{ik} + \delta FE_{jr} + \varepsilon_{kr}$$

Where $\ln w_{ikr}$ denotes the log of hourly pay of individual *i* in occupation *k* in a region *r*. DS_{kr} denotes the number of digital skills used in occupation *k* and region *r*. FE_{jr} denotes the fixed effect of one-digit occupation and regional fixed effect. We estimate the association between the utilisation of digital skills and earnings. The idea is to make use of the variation in the utilisation of digital skills among three-digit SOC after controlling for the one-digit SOC to mediate compounding effect.

Table 17 shows the impacts of digital skills on earnings. Using ASHE data, the first two columns estimate the impacts of the number of lower and higher digital skills on earnings respectively and show that both lower and higher digital skills are associated with higher earnings. The third column shows that the effect of higher digital skills dominates after including lower digital skills compared to the estimation of lower digital skills only. Columns 4 and 5 restrict the sample to the occupations requiring only lower or higher digital skills. The results are largely consistent with the results in column 1 and 2.

Table 17. Earnings effect of lower and higher digital skills.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable = log of hourly pay				
Numbers of lower digital skills	0.031***		0.014*	0.040**	
	(0.01)		(0.01)	(0.02)	
Numbers of higher digital skills		0.036***	0.029***		0.035***
		(0.01)	(0.01)		(0.01)
N	35,959	35,959	35,959	5,529	7,400

Note: All regressions have included one-digit SOC identifiers as control variables. Other control variables include age, squares of age, industry dummies, gender, and regional fixed effect. The standard errors are clustered at three-digit SOC identifiers level.
Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

Table 18 and 19 show the impacts of lower and higher-level digital skills on earnings across different occupations. When we pool digital skills together, we find that digital skills are associated with higher earnings among managers, administrative jobs, and skilled trades. When we estimate the levels of digital skills separately, the results present discrepancies. For managers, the returns to both levels of digital skills are positive but less significant. Professionals can only benefit from higher digital skills, compared to associate professionals who can only benefit from lower digital skills. The pattern is similar to administrative jobs and skilled trades. For sales, lower and higher digital skills are negatively and positively associated with earnings. The pattern is opposite to operative occupations. Similar to our previous findings, the results using ASHE data suggest that the incorporation of digital skills is endogenous. Having lower or higher level of digital skills may bring detrimental impacts on earnings.

Table 18. Effect of digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of digital skills	0.124**	0.015	0.008	0.026**	0.068***
	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
N	616	2,561	3,020	9,422	5,510
	Service occupation	Sales	Operatives		
Numbers of digital skills	0.003	-0.004	-0.024		
	(0.03)	(0.01)	(0.04)		
N	1,023	13,070	737		

Note: Table 17
Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

Table 19. Effect of basic and advanced digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of lower digital skills	0.137	-0.013	0.036**	-0.016	0.130***
	(0.16)	(0.02)	(0.02)	(0.02)	(0.02)
Numbers of higher digital skills	0.115	0.031**	-0.014	0.072***	0.028
	(0.11)	(0.01)	(0.01)	(0.03)	(0.02)
N	616	2,561	3,020	9,422	5,510
	Service occupation	Sales	Operatives		
Numbers of lower digital skills	-0.065	-0.060***	0.155**		
	(0.05)	(0.02)	(0.07)		
Numbers of higher digital skills	0.100	0.072***	-0.223***		
	(0.07)	(0.02)	(0.08)		
N	1,023	13,070	737		

Note: Table 17
Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

Overall, the ASHE analysis confirms the positive earnings differentials found of digital skills in administrative and sales roles, which had been shown in previous regressions based on the data referring to the wages of the vacancy advertised.[10] They show larger magnitudes of the coefficients in these specifications, although there are some positive effects now also found for basic digital skills, in particular in the skilled trades occupations.

7. Conclusion

Despite the widespread adoption of Information and Communication Technologies (ICT) over recent decades, the empirical literature on earnings effects resulting from the utilisation of digital skills in occupations requiring mid-range qualifications, and in apprenticeship occupations in particular, remains limited. Our analysis provides a contribution to the related evidence base making use of semi-structured (largely free text) data from apprenticeship vacancies.

After we processed these data using text mining methods to create structured database on the utilisation of digital skills in such jobs, our work shows positive associations of earnings and the utilisation of digital skills. Using Mincer-type regression models, we analyse the data in relation to three research hypotheses:

- On Hypothesis 1 about positive wage differentials associated with digital skills: We find evidence for positive wage differentials across a range of specifications, both instantaneous wage differences resulting from digital skills utilisation reported in the apprenticeship vacancies and – using data from ASHE linked at occupation level – effects over the whole working life when controlling for age and other important control variables. Where we find positive associations, they seem to be larger when looking over the whole life-course rather than the instantaneous wage differential in the apprenticeship job. However, the effects are not consistently found across the specifications and the absence of significant estimates of digital skills in the higher-level job suggests endogeneity of such skills in job roles.

[10] The estimates reported for "Operatives" suffer from small sample sizes and cannot be interpreted in the same way.

- On Hypothesis 2 on wage differentials by SOCs, our regression models have shown positive earnings associations for a range of occupations requiring mid-range qualifications and show highest impacts generally in administrative occupations and sales jobs across most specifications.
- On Hypothesis 3, which stipulates that higher-level skills drive the overall wage returns, our work provides evidence that positive earnings differentials are largely driven by advanced skills, while mentioning explicitly lower-level digital skills like Microsoft Office, computers, email, and social media in many specifications exhibit negative correlations with observed wages. While there are some benefits to life-course earnings found in the analysis of ASHE data for lower-level digital skills, these are limited skilled trades and operative occupations and have not been found in the data from apprenticeship vacancies.

From a practical point of view, the evidence gained from our work should be taken on board in the further development of Apprenticeship Standards and related education programmes as existing Standards will be subject to review over the coming years. Indeed, many apprenticeships did include some education related to Information and Communication Technologies (ICT), often aligned to Functional Skills at Level 2. Instead of being occupation-specific however, Functional Skills – previously known as "Skills for Life" – are focusing on managing life in the digital era, i.e. are more related to digital inclusion than job roles. Of course, education enhancing digital inclusion must be a key priority to make sure the opportunities of the computer age can be accessed by the wider population, to avoid social exclusion in a world increasingly requiring some digital skills and to manage new resulting from this.

However, low-level digital skills won't result in significant earnings effects based on the findings presented here. In our view, to improve workforce skills for occupations requiring mid-level qualifications requires relatively more advanced digital skills: general and professional software, computing and computing languages. Lower-level digital skills like Microsoft Office, computers, email and social media have become an expected minimum level of digital literacy, which is not associated with a ceteris paribus wage differential, and the learning of digital skills in apprenticeship programmes would need to go beyond this to achieve the returns to human capital investment in digital skills.

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Appendix Tables and Figures

Table A1. Selection of standards for description of individual occupations.

	Vacancies	Number of standards	% of total
Vacancies since Aug-2018			
Old “framework” vacancies	132,567	0	31%
Vacancies aligned to “Standards”	301,232	391	69%
Total	433,799		
Description of subgroups			
All with 10+ vacancies	300,920	316	69%
of all standards	99.90%		
All with 30+ vacancies	300,017	266	69%
of all standards	99.60%		
All with 50+ vacancies	298,698	232	69%
of all standards	99.16%		

Source: https://www.gov.uk/apply-apprenticeship.

Table A2. Routes and digital skills (percentage).

Panel A, Intermediate apprenticeships

Route	General software	Professional software	Microsoft and office	Computing	Computing language	Computers	Digital	Emails	Social media	Data
Agriculture, environmental	1.00%	0.00%	2.00%	1.00%	0.00%	11.00%	4.00%	1.00%	0.00%	1.00%
Business and administration	2.00%	0.00%	25.00%	4.00%	0.00%	26.00%	10.00%	13.00%	8.00%	34.00%
Care services	1.00%	0.00%	2.00%	4.00%	0.00%	4.00%	2.00%	1.00%	0.00%	5.00%
Catering and hospitality	0.00%	0.00%	1.00%	1.00%	0.00%	2.00%	8.00%	0.00%	0.00%	0.00%
Construction	0.00%	0.00%	4.00%	2.00%	0.00%	8.00%	2.00%	1.00%	0.00%	2.00%
Creative and design	-	-	-	-	-	-	-	-	-	-
Digital	-	-	-	-	-	-	-	-	-	-
Education and childcare	-	-	-	-	-	-	-	-	-	-
Engineering and manufacturing	2.00%	0.00%	1.00%	3.00%	0.00%	9.00%	1.00%	0.00%	0.00%	3.00%
Hair and beauty	0.00%	0.00%	0.00%	0.00%	0.00%	7.00%	1.00%	0.00%	0.00%	0.00%
Health and science	5.00%	0.00%	9.00%	2.00%	0.00%	19.00%	1.00%	3.00%	0.00%	3.00%
Legal, finance and accounting	0.00%	0.00%	25.00%	1.00%	0.00%	34.00%	8.00%	14.00%	0.00%	7.00%
Protective services	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Sales, marketing	3.00%	0.00%	18.00%	1.00%	0.00%	30.00%	13.00%	13.00%	1.00%	19.00%
Transport and logistics	2.00%	0.00%	6.00%	1.00%	0.00%	13.00%	6.00%	1.00%	4.00%	4.00%

Panel B, Advanced apprenticeships

Route	General software	Professional software	Microsoft and office	Computing	Computing language	Computers	Digital	Emails	Social media	Data
Agriculture, environmental	0.00%	0.00%	1.00%	0.00%	0.00%	4.00%	1.00%	0.00%	0.00%	1.00%
Business and administration	8.00%	0.00%	41.00%	2.00%	0.00%	36.00%	10.00%	22.00%	2.00%	35.00%
Care services	1.00%	0.00%	3.00%	1.00%	0.00%	19.00%	0.00%	0.00%	1.00%	5.00%
Catering and hospitality	0.00%	0.00%	3.00%	1.00%	0.00%	6.00%	16.00%	0.00%	0.00%	3.00%
Construction	10.00%	3.00%	7.00%	7.00%	1.00%	13.00%	6.00%	2.00%	0.00%	13.00%
Creative and design	25.00%	0.00%	19.00%	2.00%	1.00%	43.00%	49.00%	11.00%	22.00%	9.00%
Digital	54.00%	4.00%	21.00%	24.00%	13.00%	50.00%	21.00%	10.00%	1.00%	32.00%
Education and childcare	1.00%	0.00%	3.00%	3.00%	0.00%	5.00%	1.00%	1.00%	0.00%	8.00%
Engineering and manufacturing	3.00%	1.00%	3.00%	3.00%	0.00%	7.00%	1.00%	0.00%	0.00%	5.00%
Hair and beauty	0.00%	0.00%	0.00%	0.00%	0.00%	4.00%	44.00%	0.00%	0.00%	0.00%
Health and science	2.00%	0.00%	10.00%	2.00%	0.00%	8.00%	1.00%	2.00%	0.00%	15.00%
Legal, finance and accounting	7.00%	0.00%	42.00%	4.00%	0.00%	22.00%	6.00%	13.00%	0.00%	23.00%
Protective services	1.00%	0.00%	7.00%	2.00%	0.00%	56.00%	15.00%	39.00%	0.00%	9.00%
Sales, marketing	15.00%	0.00%	23.00%	2.00%	1.00%	48.00%	47.00%	24.00%	23.00%	20.00%
Transport and logistics	4.00%	0.00%	21.00%	2.00%	0.00%	34.00%	4.00%	26.00%	0.00%	16.00%

Notes: The table shows the percentages of vacancies containing different digital skills.

Panel C, Higher apprenticeships

Route	General software	Professional software	Microsoft and office	Computing	Computing language	Computers	Digital	Emails	Social media	Data
Agriculture, environmental	7.00%	0.00%	19.00%	0.00%	2.00%	2.00%	10.00%	0.00%	0.00%	29.00%
Business and administration	2.00%	0.00%	11.00%	2.00%	0.00%	7.00%	6.00%	2.00%	1.00%	14.00%
Care services	0.00%	0.00%	0.00%	0.00%	0.00%	1.00%	0.00%	0.00%	0.00%	3.00%
Catering and hospitality	2.00%	0.00%	3.00%	0.00%	0.00%	6.00%	0.00%	0.00%	0.00%	2.00%
Construction	12.00%	4.00%	10.00%	1.00%	1.00%	8.00%	4.00%	2.00%	0.00%	8.00%
Creative and design	-	-	-	-	-	-	-	-	-	-
Digital	46.00%	13.00%	13.00%	28.00%	13.00%	33.00%	25.00%	2.00%	2.00%	49.00%
Education and childcare	-	-	-	-	-	-	-	-	-	-
Engineering and manufacturing	11.00%	1.00%	7.00%	7.00%	3.00%	8.00%	8.00%	1.00%	3.00%	9.00%
Hair and beauty	-	-	-	-	-	-	-	-	-	-
Health and science	0.00%	0.00%	1.00%	3.00%	6.00%	7.00%	18.00%	0.00%	0.00%	11.00%
Legal, finance and accounting	0.00%	6.00%	28.00%	1.00%	0.00%	1.00%	3.00%	4.00%	0.00%	26.00%
Protective services	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Sales, marketing	4.00%	0.00%	14.00%	0.00%	0.00%	14.00%	14.00%	8.00%	7.00%	14.00%
Transport and logistics	-	-	-	-	-	-	-	-	-	-

Notes: The table shows the percentages of vacancies containing different digital skills.
Source: https://www.gov.uk/apply-apprenticeship.

Table A3. Digital skills demanded by SOC occupations (frequency).

Occupations	General software	Professional software	Microsoft and office	Computing	Computing language	Computers	Digital	Emails	Social media	Data
Managers	0.03	0	0.044	0.004	0.003	0.041	0.028	0.009	0.007	0.062
Professional occupations	0.288	0.071	0.165	0.18	0.086	0.242	0.182	0.047	0.02	0.318
Associate professional and technical occupations	0.093	0.007	0.136	0.026	0.007	0.242	0.192	0.09	0.085	0.144
Administrative and secretarial occupations	0.079	0.001	0.409	0.026	0.003	0.346	0.089	0.205	0.017	0.324
Skilled trades occupations	0.009	0.001	0.012	0.016	0.001	0.04	0.051	0.003	0	0.013
Caring, leisure and other service occupations	0.019	0	0.039	0.02	0.003	0.08	0.024	0.019	0.001	0.045
Sales and customer service occupations	0.03	0	0.178	0.011	0.001	0.313	0.124	0.13	0.01	0.182
Process, plant and machine operatives	0.01	0	0.047	0.021	0	0.103	0.016	0.004	0	0.054
Elementary occupations	0.017	0	0.062	0.014	0.005	0.136	0.062	0.009	0.041	0.038

Source: https://www.gov.uk/apply-apprenticeship.

Table A4. Earnings effect of lower and higher digital skills.

	(1)	(2)	(3)	(4)	(5)
		Dependent variable = log of hourly pay			
Numbers of lower digital skills	0.104***		0.057***	0.291	0.000
	(0.01)		(0.01)	(0.44)	(.)
Numbers of higher digital skills		0.084***	0.050***	0.000	-0.383
		(0.01)	(0.01)	(.)	(0.52)
N	48301	48301	48301	546	1055

Note: All regressions have included one-digit SOC identifiers as control variables. Other control variables include age, squares of age, industry dummies, gender, and regional fixed effect. The standard errors are clustered at three-digit SOC identifiers level.
Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

Table A5. Effect of digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of digital skills	0.306***	0.029***	0.030***	0.127***	0.170***
	(0.11)	(0.01)	(0.01)	(0.02)	(0.02)
N	1064	4286	4831	11189	7581
	Service occupation	Sales	Operatives		
Numbers of digital skills	0.318*	-0.000	0.008		
	(0.18)	(0.01)	(0.04)		
N	1490	14707	3153		

Note: Table A4
Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

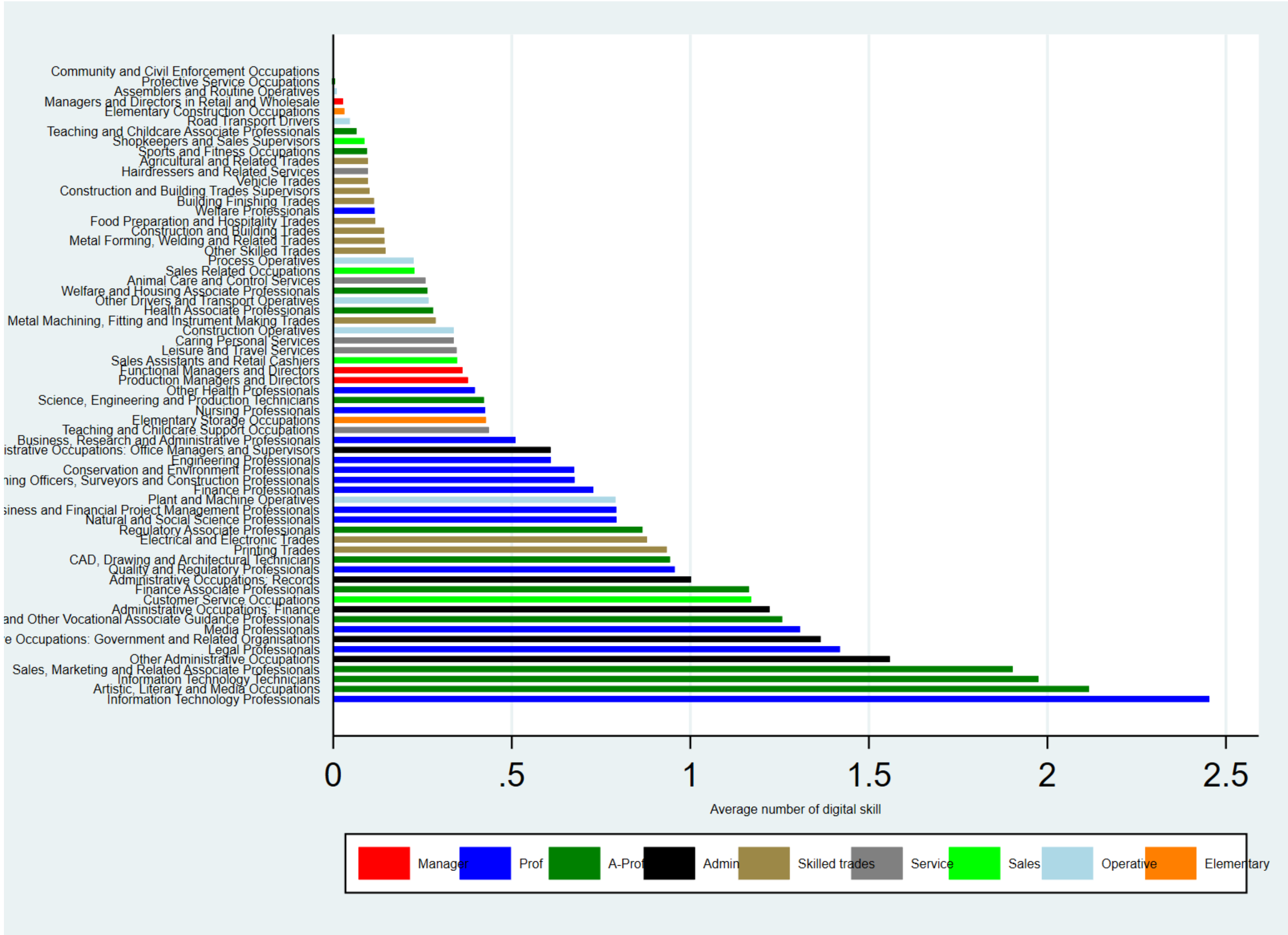
Table A6. Effect of basic and advanced digital skills on wages.

	(1) Manager	(2) Professional	(3) Associate professional	(4) Admin.	(5) Skilled trades
Numbers of lower digital skills	3.046***	0.065**	0.547***	0.041	0.871***
	(0.61)	(0.03)	(0.05)	(0.04)	(0.08)
Numbers of higher digital skills	-1.729***	0.013	-0.338***	0.212***	-0.067**
	(0.46)	(0.01)	(0.03)	(0.04)	(0.03)
N	1064	4286	4831	11189	7581
	Service occupation	Sales	Operatives		
Numbers of lower digital skills	0.268	-0.111***	0.015		
	(0.18)	(0.02)	(0.08)		
Numbers of higher digital skills	0.823*	0.158***	0.002		
	(0.45)	(0.03)	(0.08)		
N	1490	14707	3153		

Note: Table A4

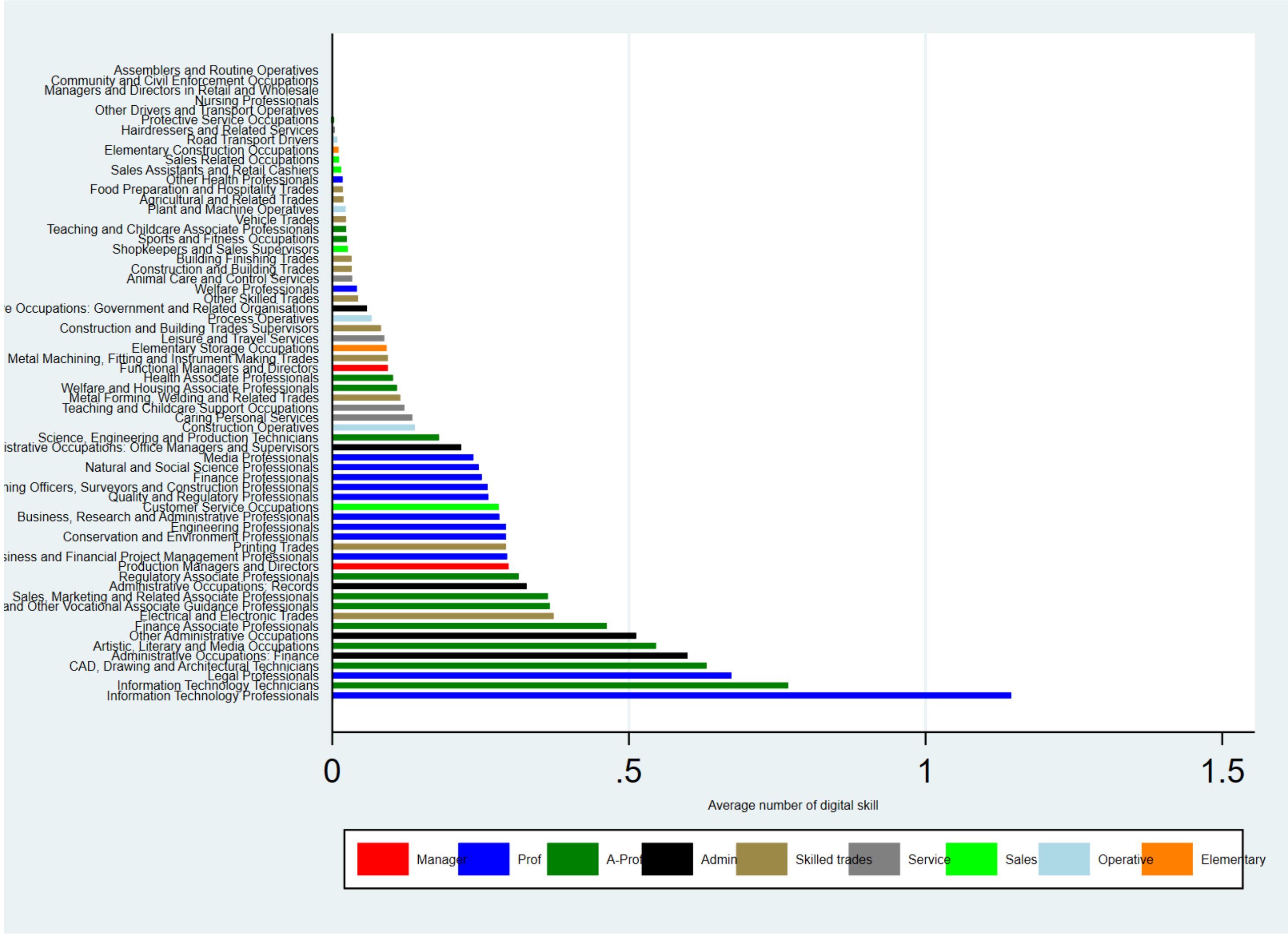
Source: Annual Survey of Hours and Earnings 2020/21 data; own calculations

Figure A1. Number of digital skills by occupations.



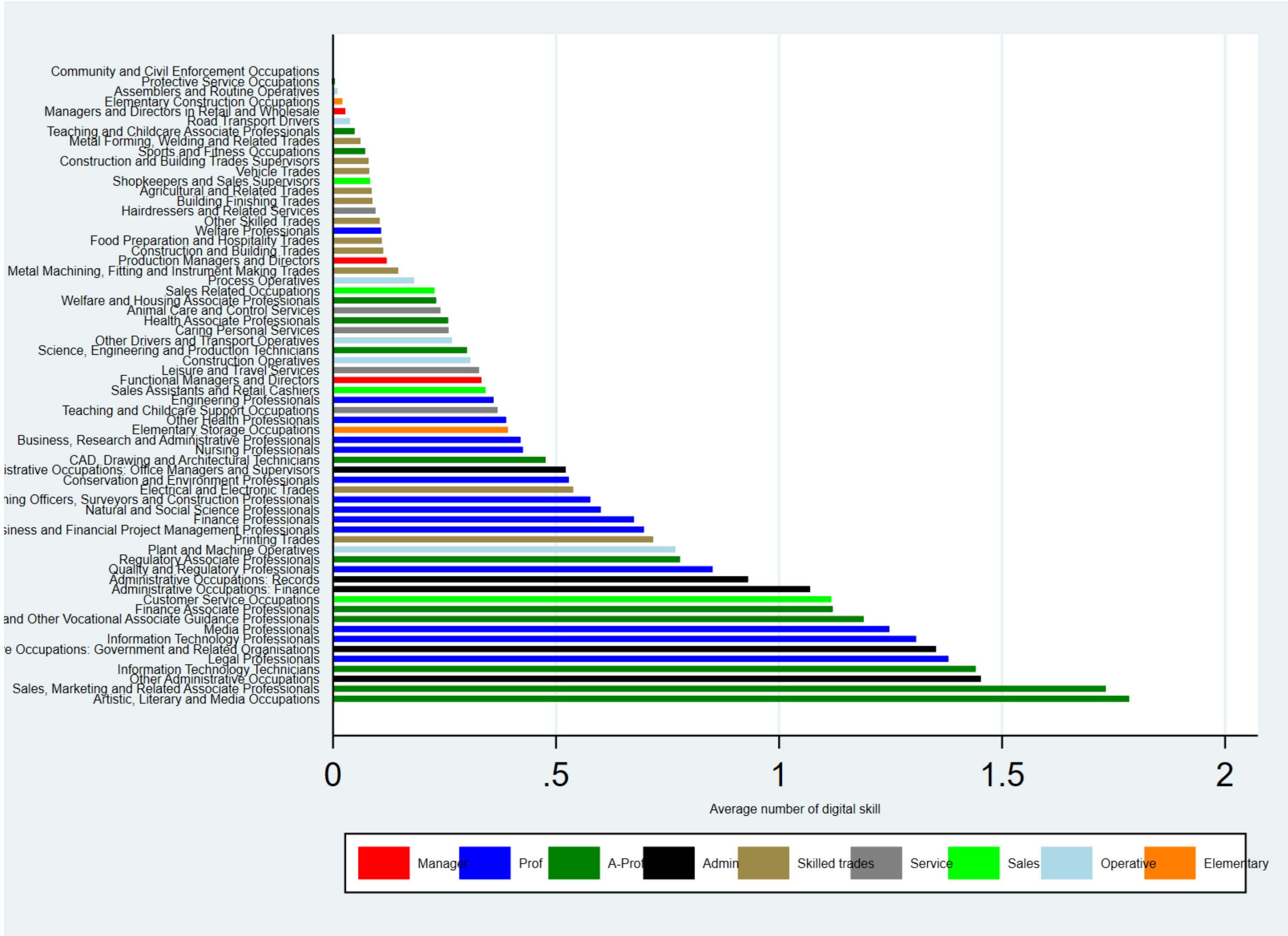
Source: https://www.gov.uk/apply-apprenticeship.

Figure A2. Number of advanced digital skills by occupations



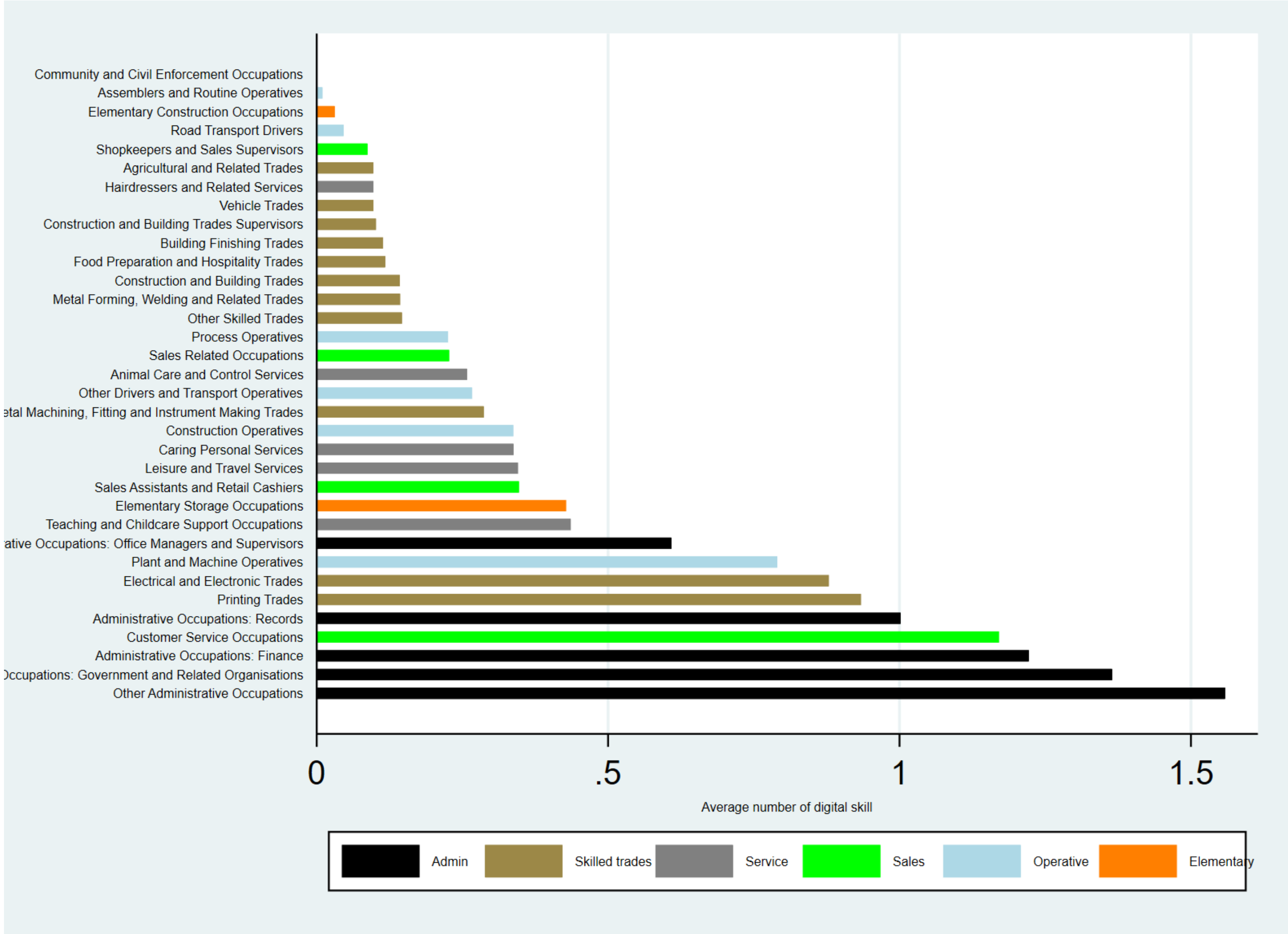
Source: https://www.gov.uk/apply-apprenticeship.

Figure A3. Number of basic digital skills by occupations.



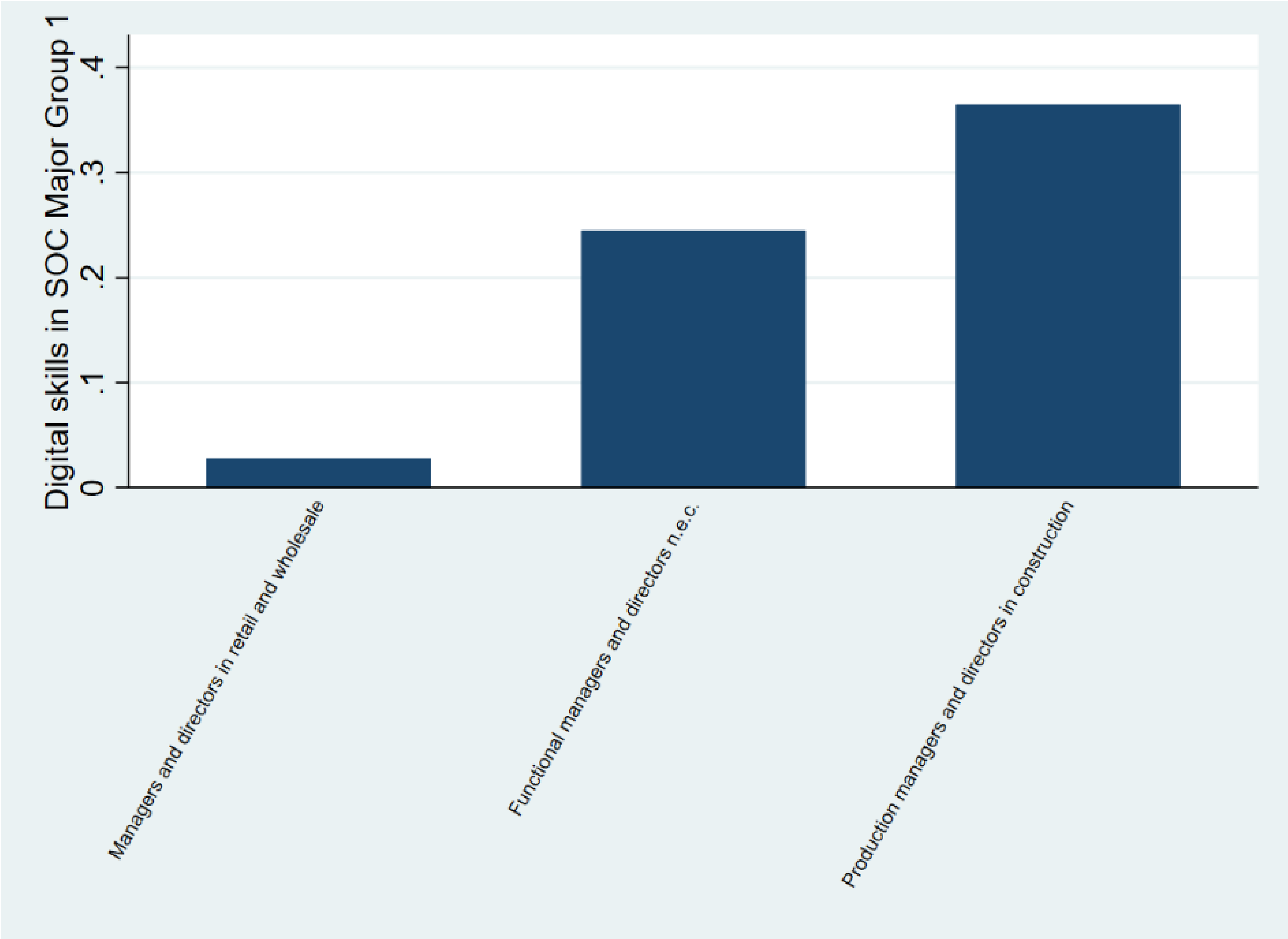
Source: https://www.gov.uk/apply-apprenticeship.

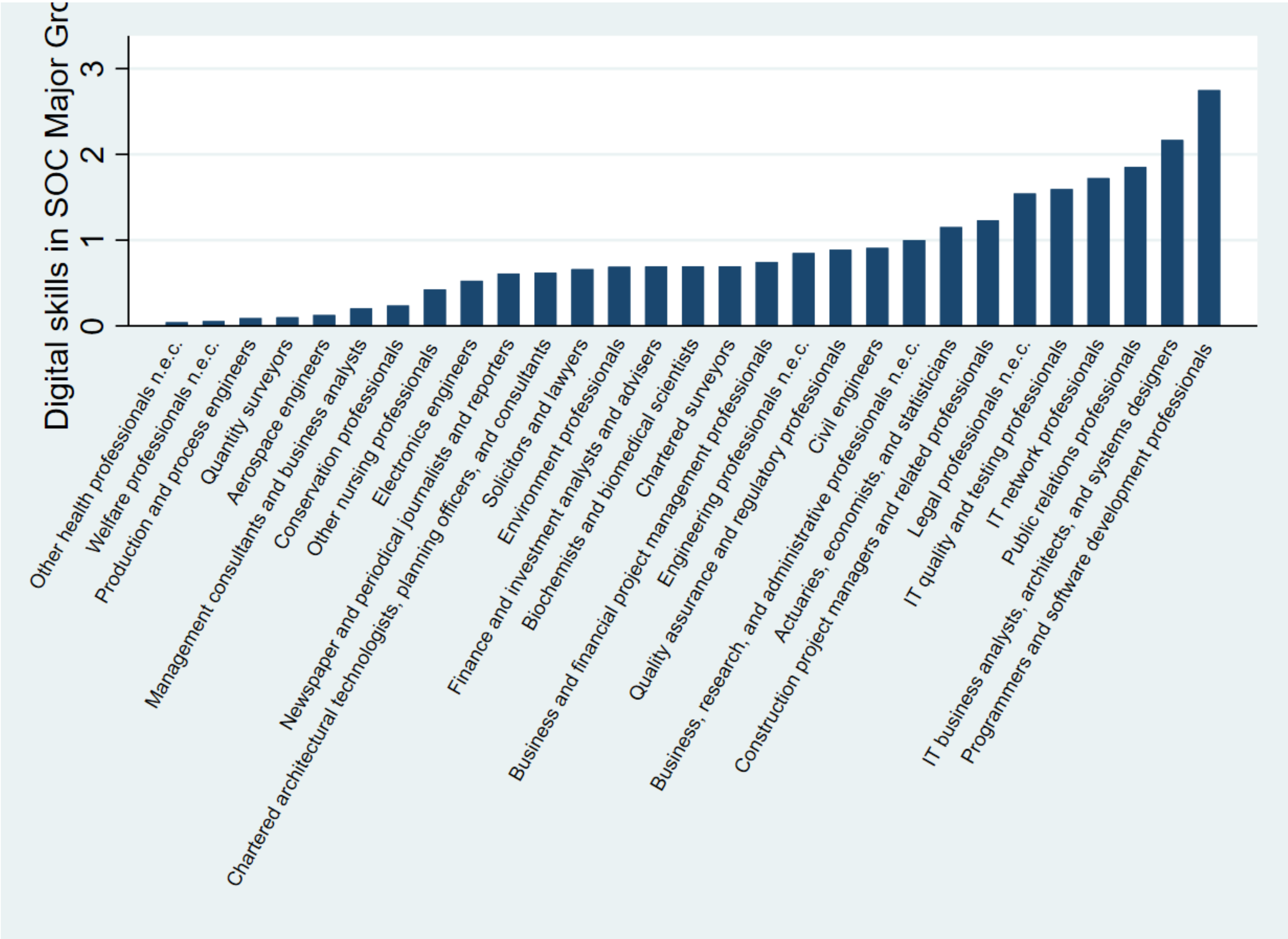
Figure A4. Number of digital skills in lower ranked occupations.

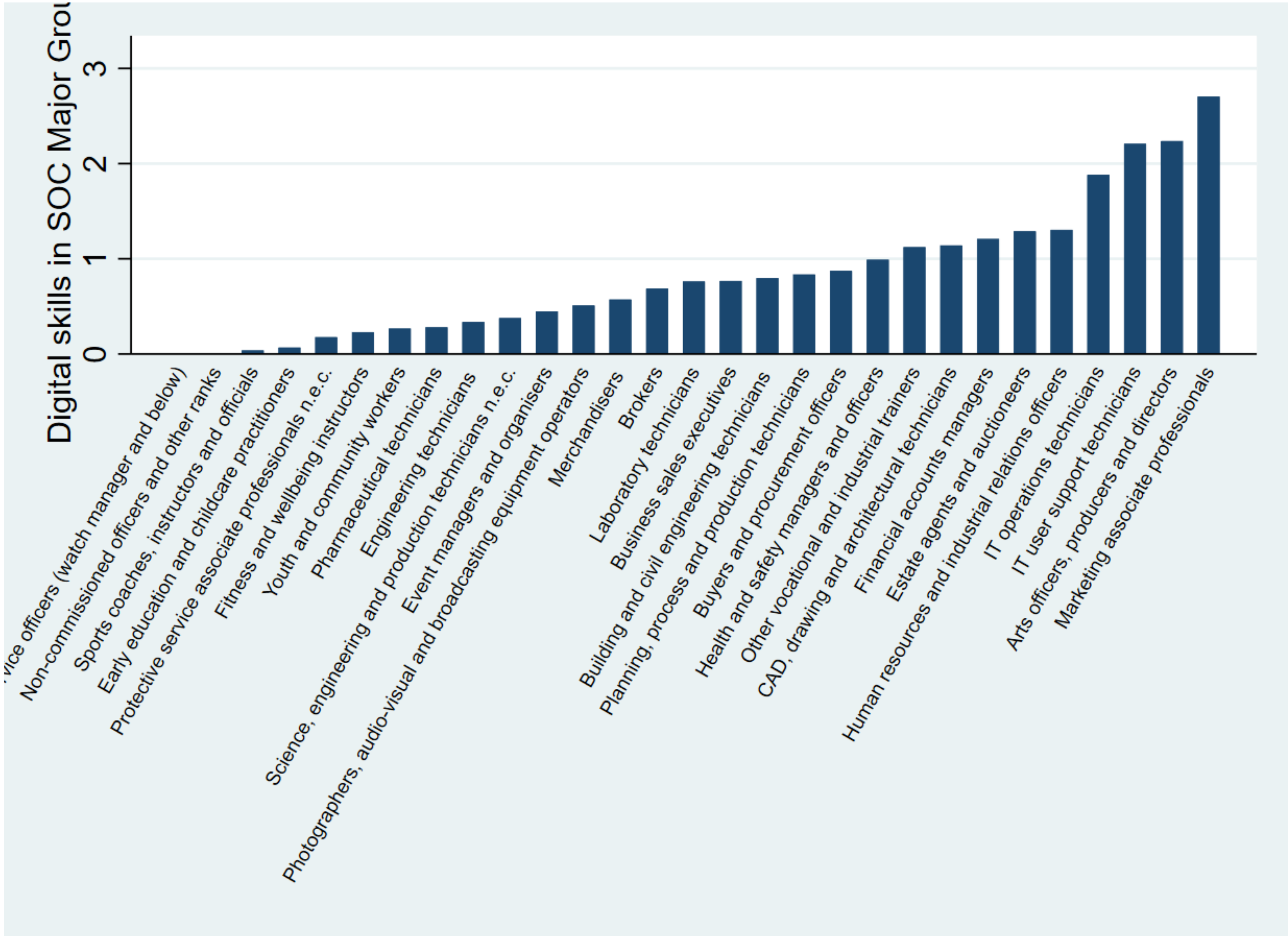


Source: https://www.gov.uk/apply-apprenticeship.

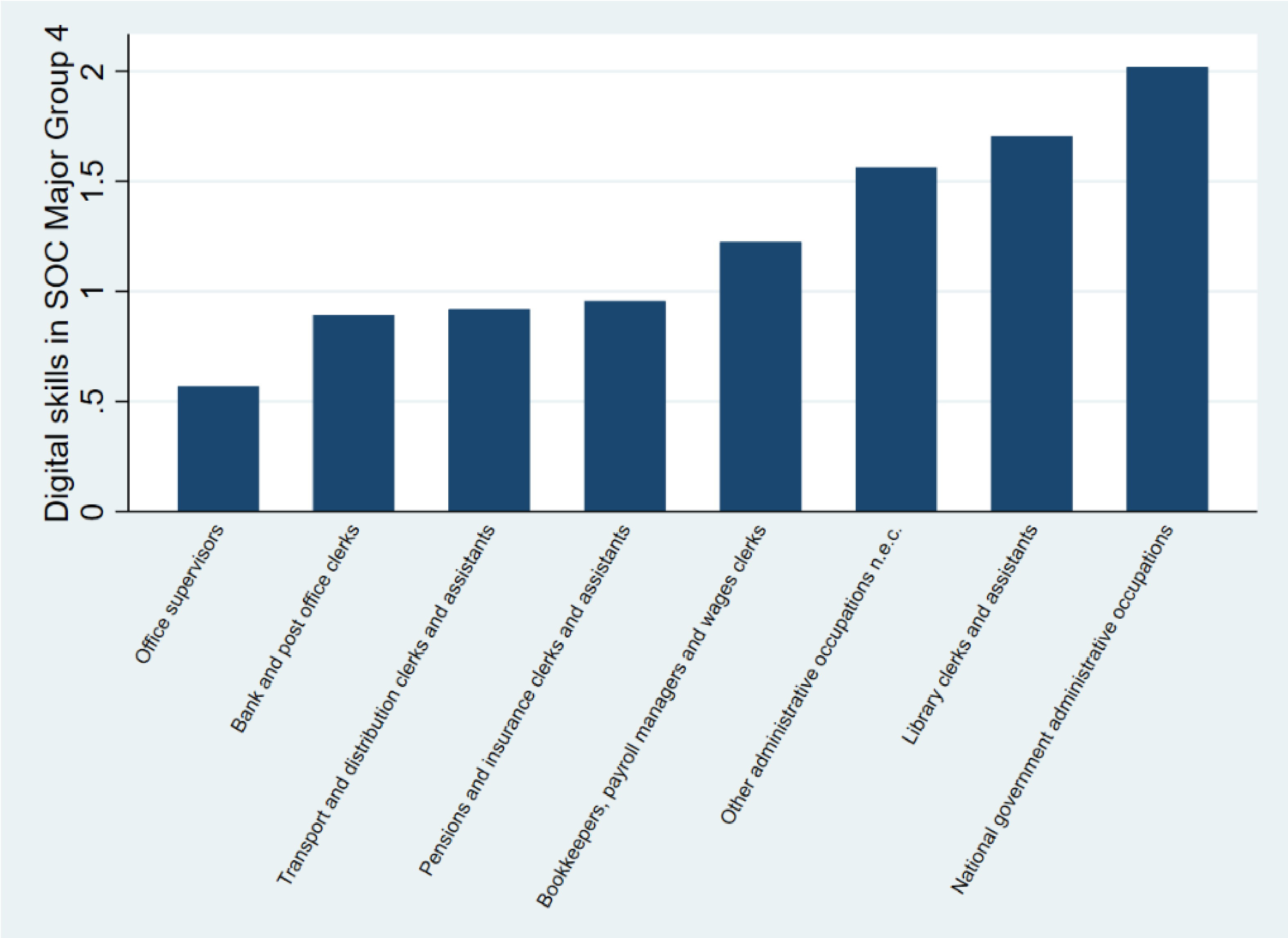
Figure A5. Digital skills in SOC Major Groups.

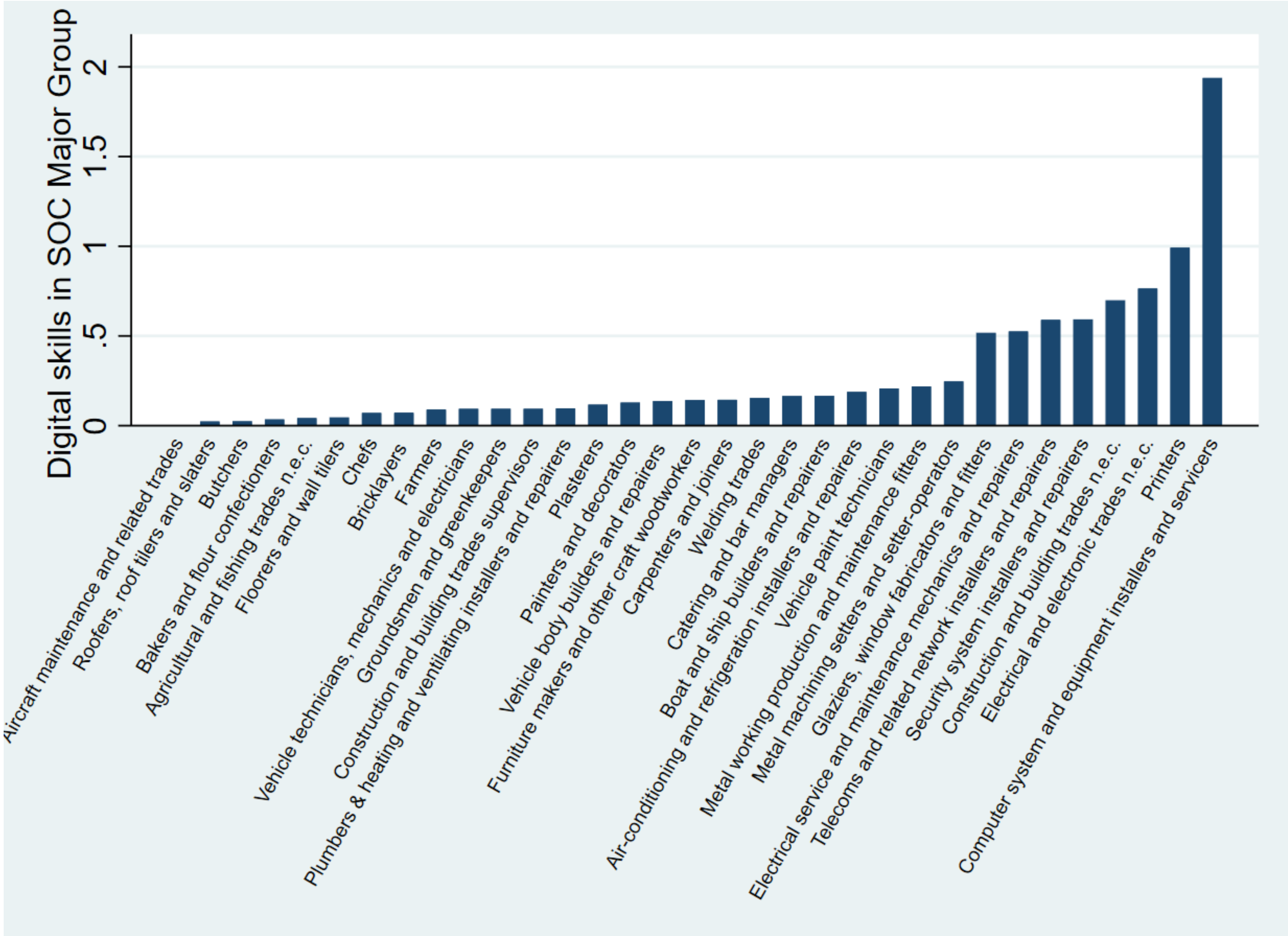



Digital skills in SOC Major Gro
0
1
2
3
Other health professionals n.e.c.
Welfare professionals n.e.c.
Production and process engineers
Quantity surveyors
Aerospace engineers
Management consultants and business analysts
Conservation professionals
Other nursing professionals
Electronics engineers
Newspaper and periodical journalists and reporters
Chartered architectural technologists, planning officers, and consultants
Solicitors and lawyers
Environment professionals
Finance and investment analysts and advisers
Biochemists and biomedical scientists
Chartered surveyors
Business and financial project management professionals
Engineering professionals n.e.c.
Quality assurance and regulatory professionals
Civil engineers
Business, research, and administrative professionals n.e.c.
Actuaries, economists, and statisticians
Construction project managers and related professionals
Legal professionals n.e.c.
IT quality and testing professionals
IT network professionals
Public relations professionals
IT business analysts, architects, and systems designers
Programmers and software development professionals

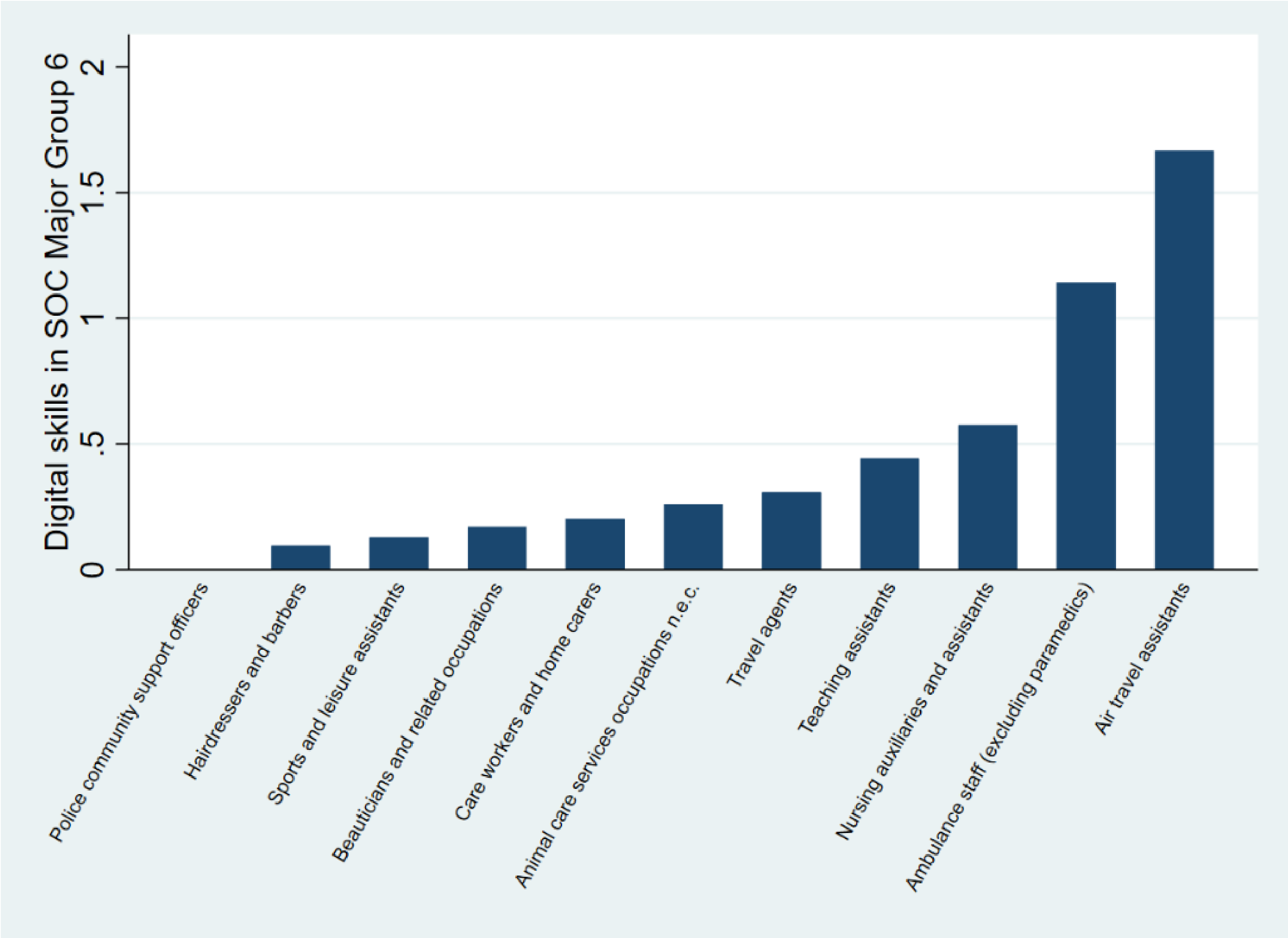


Digital skills in SOC Major Grou
0
1
2
3
Non-commissioned officers and other ranks
Sports coaches, instructors and officials
Early education and childcare practitioners
Protective service associate professionals n.e.c.
Fitness and wellbeing instructors
Youth and community workers
Pharmaceutical technicians
Engineering technicians
Science, engineering and production technicians n.e.c.
Event managers and organisers
Photographers, audio-visual and broadcasting equipment operators
Merchandisers
Brokers
Laboratory technicians
Business sales executives
Building and civil engineering technicians
Planning, process and production technicians
Buyers and procurement officers
Health and safety managers and officers
Other vocational and industrial trainers
CAD, drawing and architectural technicians
Financial accounts managers
Estate agents and auctioneers
Human resources and industrial relations officers
IT operations technicians
IT user support technicians
Arts officers, producers and directors
Marketing associate professionals

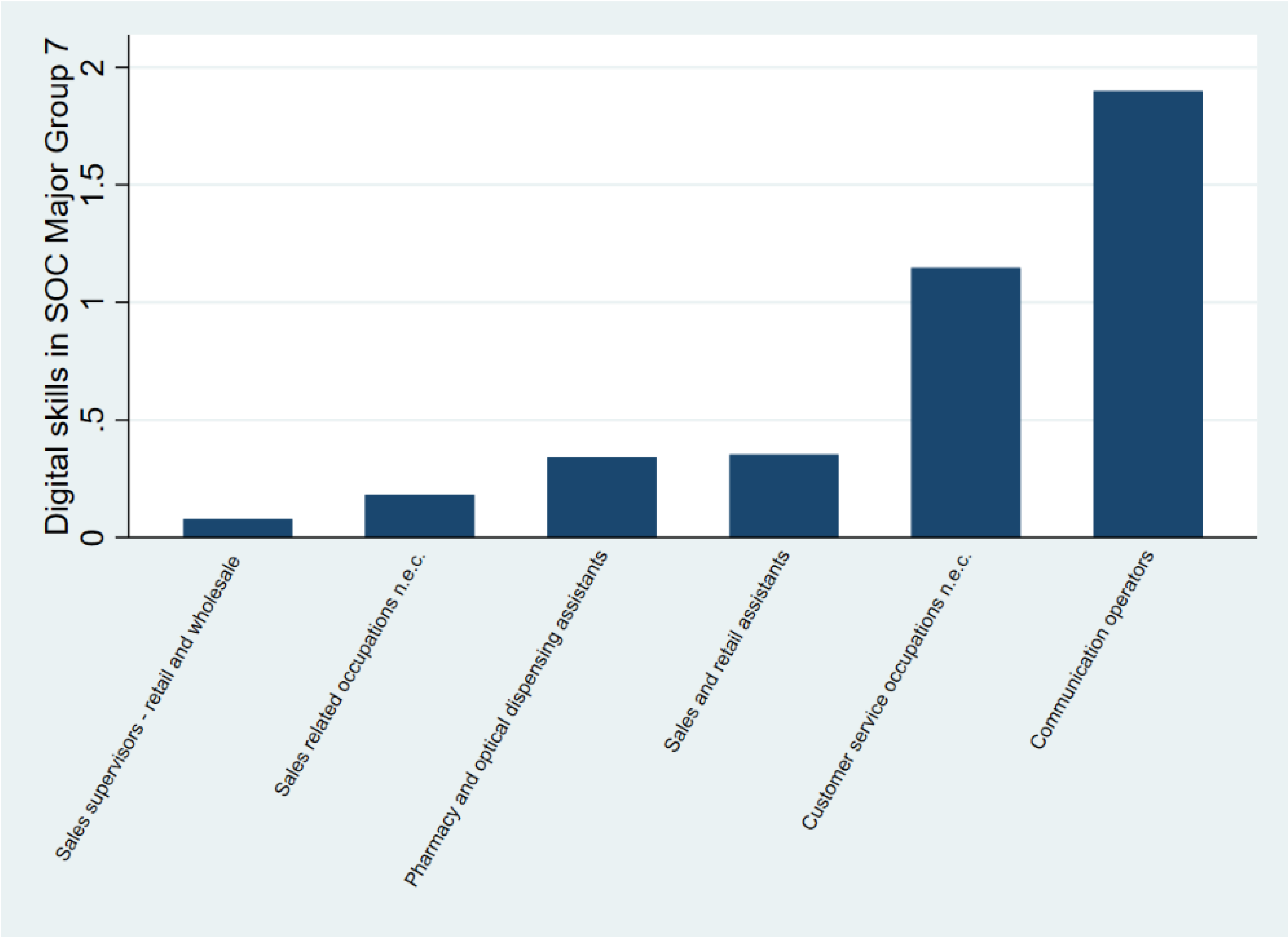

Digital skills in SOC Major Group 4
0
.5
1
1.5
2
Office supervisors
Bank and post office clerks
Transport and distribution clerks and assistants
Pensions and insurance clerks and assistants
Bookkeepers, payroll managers and wages clerks
Other administrative occupations n.e.c.
Library clerks and assistants
National government administrative occupations

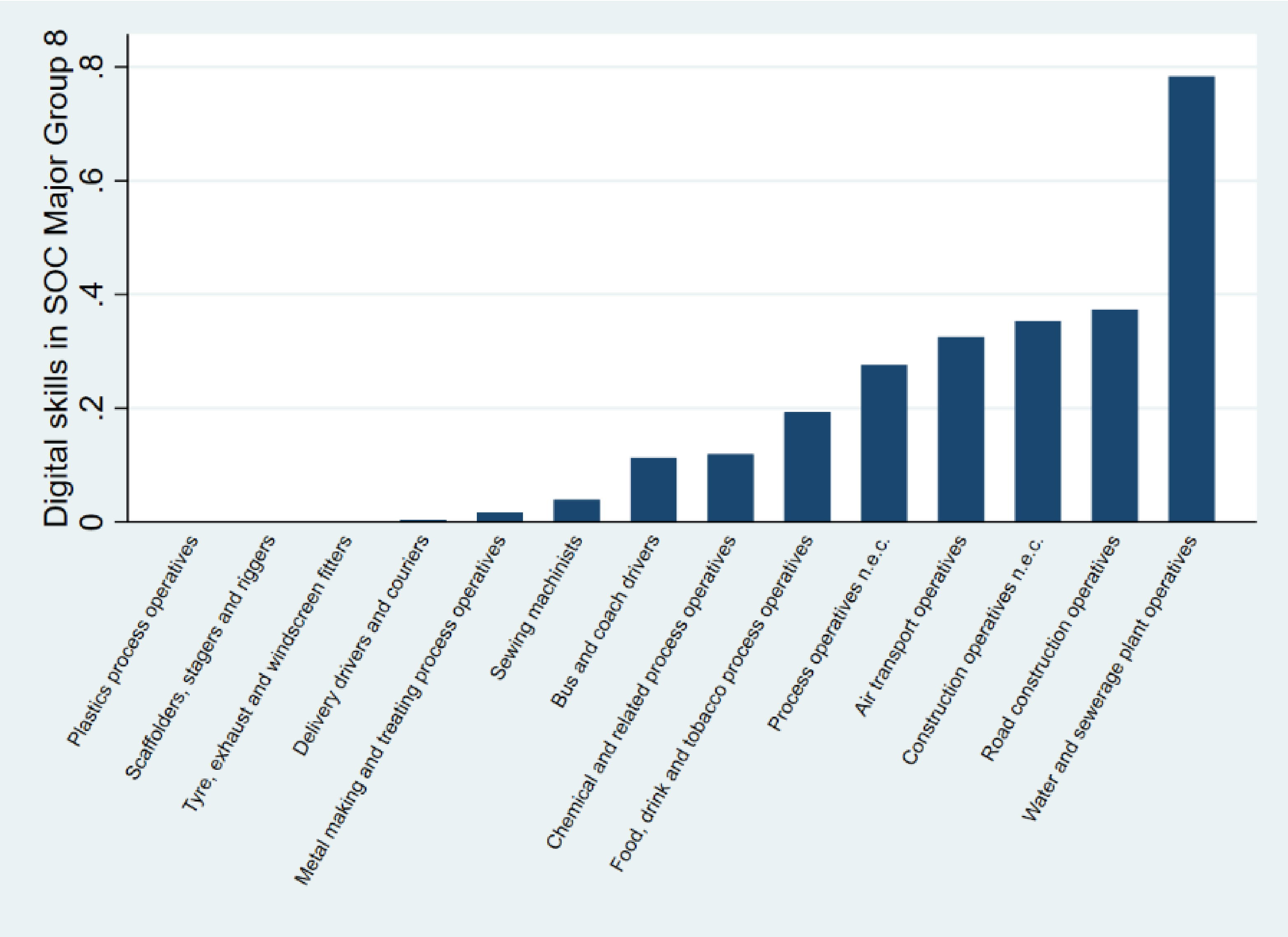


Digital skills in SOC Major Group
0
.5
1
1.5
2
Aircraft maintenance and related trades
Roofers, roof tilers and slaters
Butchers
Bakers and flour confectioners
Agricultural and fishing trades n.e.c.
Floorers and wall tilers
Chefs
Bricklayers
Farmers
Vehicle technicians, mechanics and electricians
Groundsmen and greenkeepers
Construction and building trades supervisors
Plumbers & heating and ventilating installers and repairers
Plasterers
Painters and decorators
Vehicle body builders and repairers
Furniture makers and other craft woodworkers
Carpenters and joiners
Welding trades
Catering and bar managers
Boat and ship builders and repairers
Air-conditioning and refrigeration installers and repairers
Vehicle paint technicians
Metal working production and maintenance fitters
Metal machining setters and setter-operators
Glaziers, window fabricators and fitters
Electrical service and maintenance mechanics and repairers
Telecoms and related network installers and repairers
Security system installers and repairers
Construction and building trades n.e.c.
Electrical and electronic trades n.e.c.
Printers
Computer system and equipment installers and servicers



Digital skills in SOC Major Group 6
0
.5
1
1.5
2
Police community support officers
Hairdressers and barbers
Sports and leisure assistants
Beauticians and related occupations
Care workers and home carers
Animal care services occupations n.e.c.
Travel agents
Teaching assistants
Nursing auxiliaries and assistants
Ambulance staff (excluding paramedics)
Air travel assistants


Digital skills in SOC Major Group 7
0
.5
1
1.5
2
Sales supervisors - retail and wholesale
Sales related occupations n.e.c.
Pharmacy and optical dispensing assistants
Sales and retail assistants
Customer service occupations n.e.c.
Communication operators



Digital skills in SOC Major Group 8
0
.2
.4
.6
.8
Plastics process operatives
Scaffolders, stagers and riggers
Tyre, exhaust and windscreen fitters
Delivery drivers and couriers
Metal making and treating process operatives
Sewing machinists
Bus and coach drivers
Chemical and related process operatives
Food, drink and tobacco process operatives
Process operatives n.e.c.
Air transport operatives
Construction operatives n.e.c.
Road construction operatives
Water and sewerage plant operatives

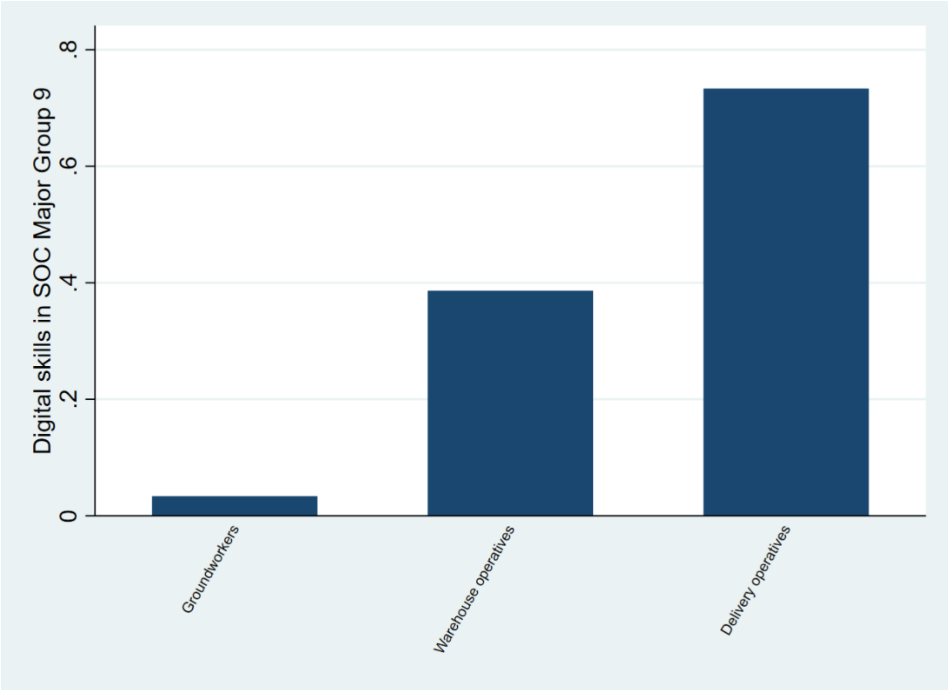
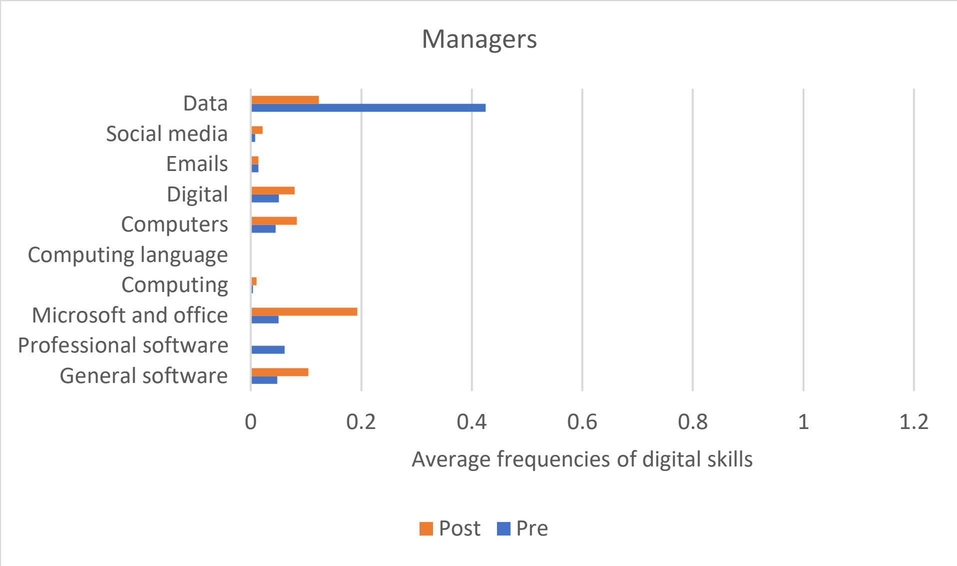
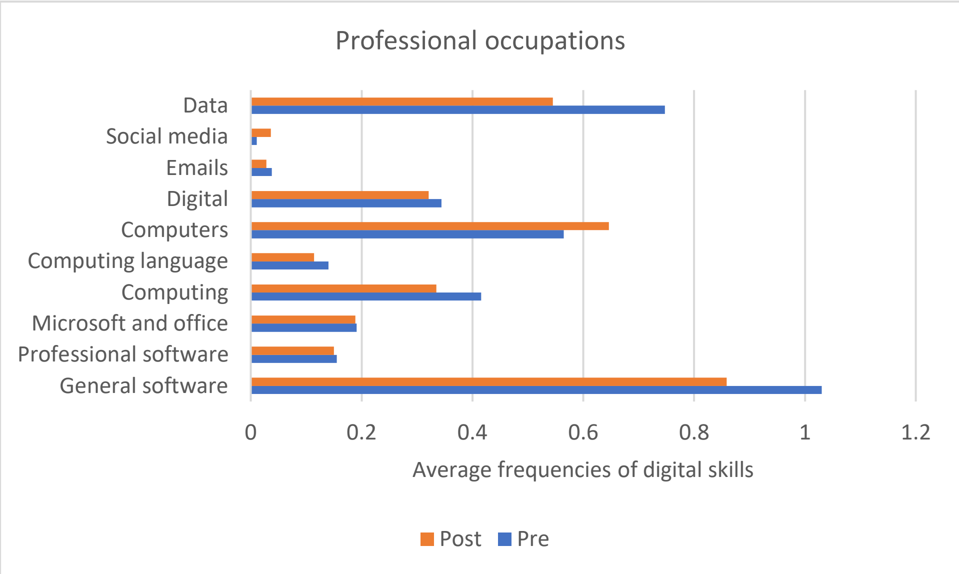
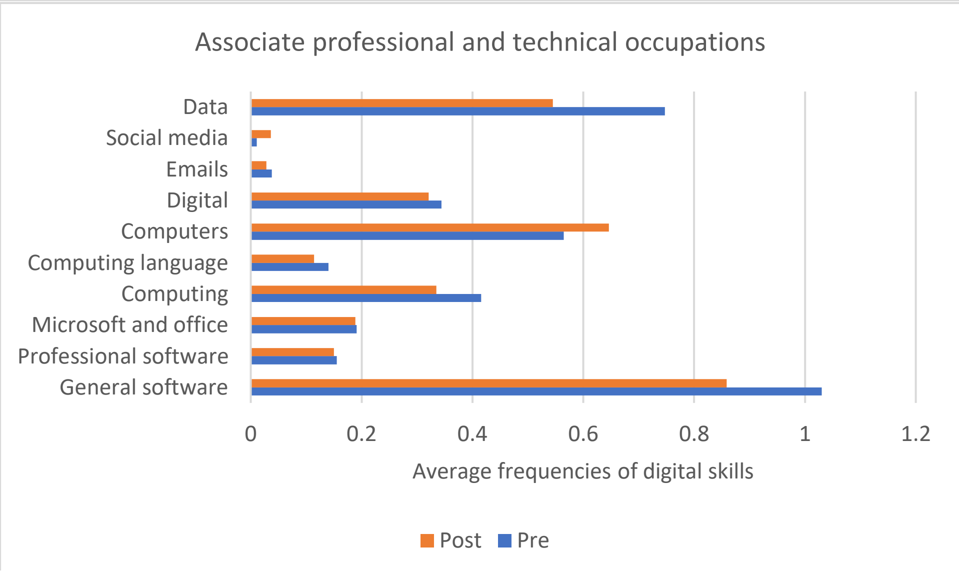

Digital skills in SOC Major Group 9
0
.2
.4
.6
.8
Groundworkers
Warehouse operatives
Delivery operatives

Figure A6. Digital skills by SOC major groups (average frequencies, before and after the Covid-19 Pandemic*).



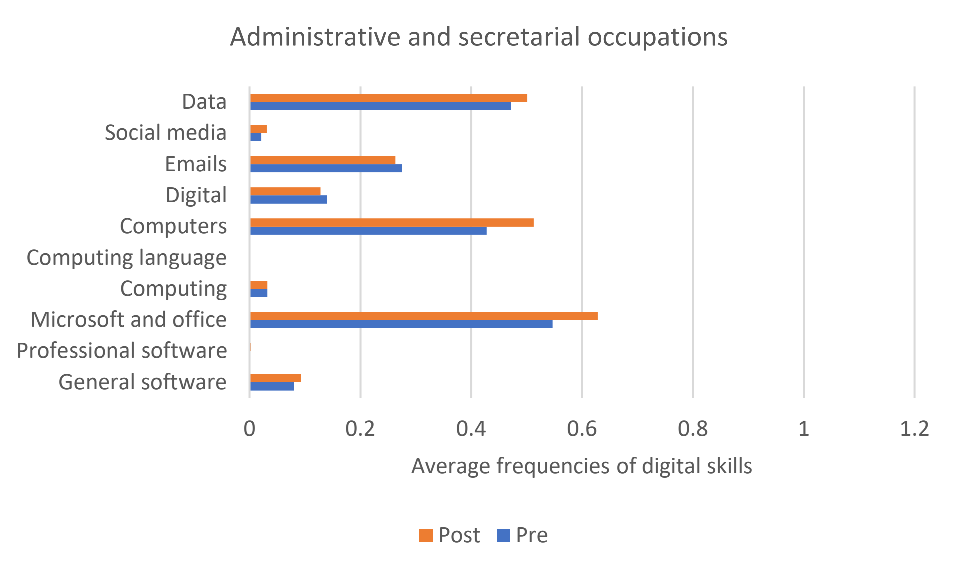


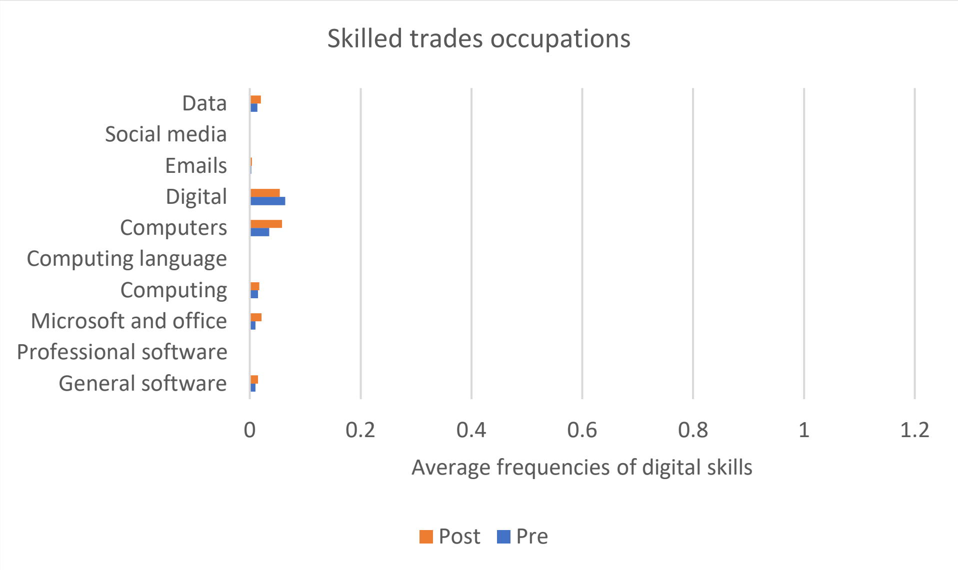


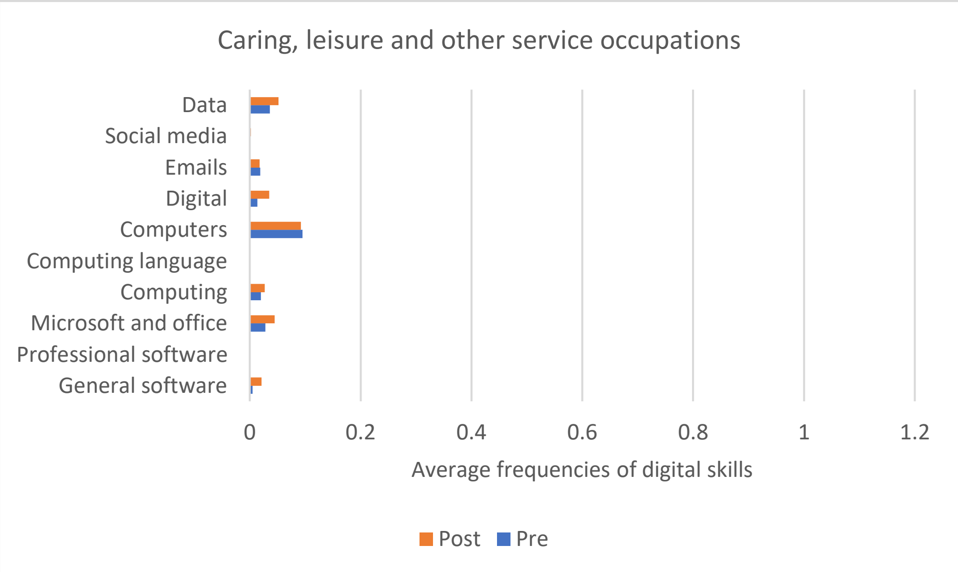
* Up-to/including Q1/2020 and from/including Q3/2020

Source: https://www.gov.uk/apply-apprenticeship`

Figure A6 (cont.). Digital skills by SOC major groups (average frequencies, before and after the Covid-19 Pandemic[*]).



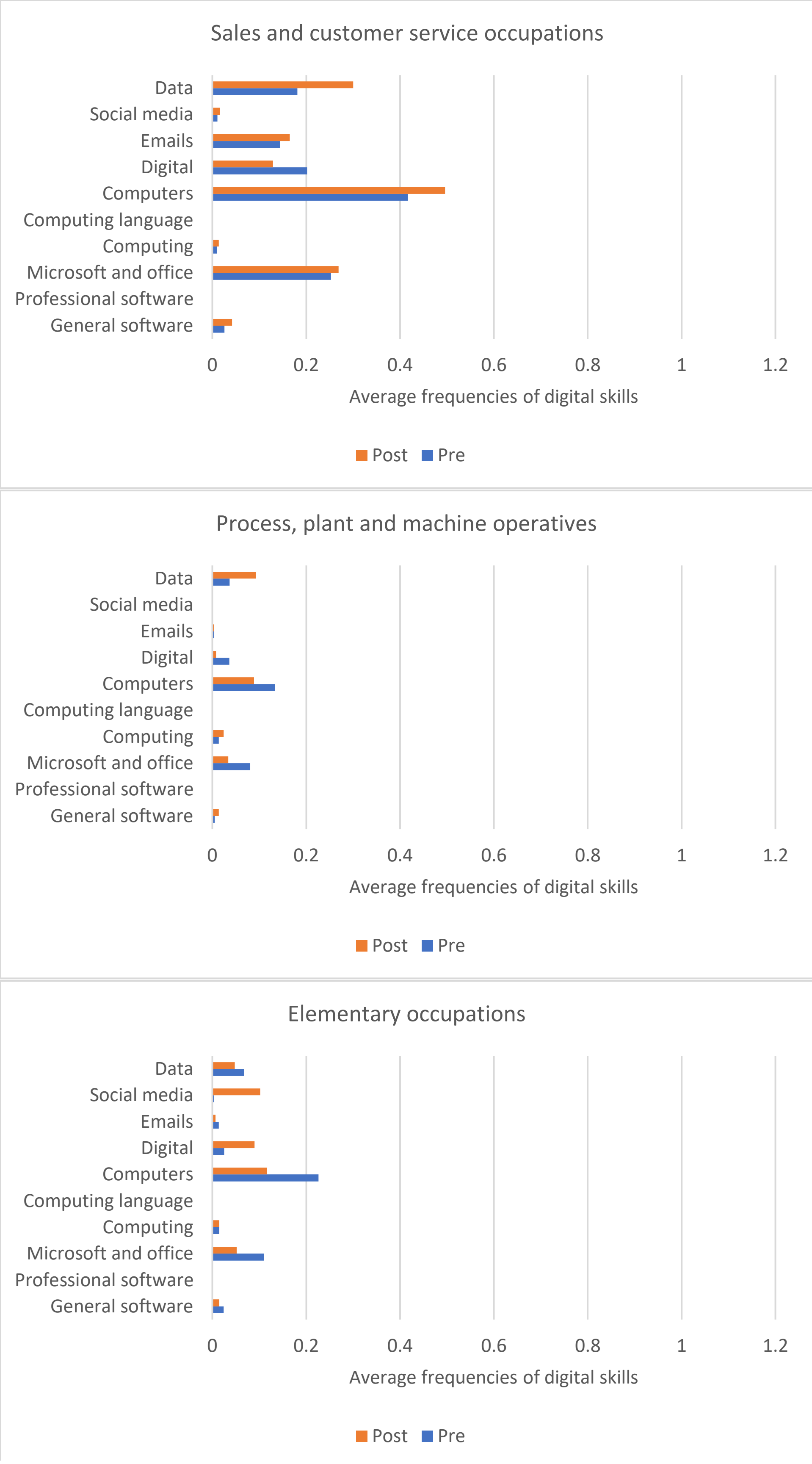




[*] Up-to/including Q1/2020 and from/including Q3/2020

Source: https://www.gov.uk/apply-apprenticeship`

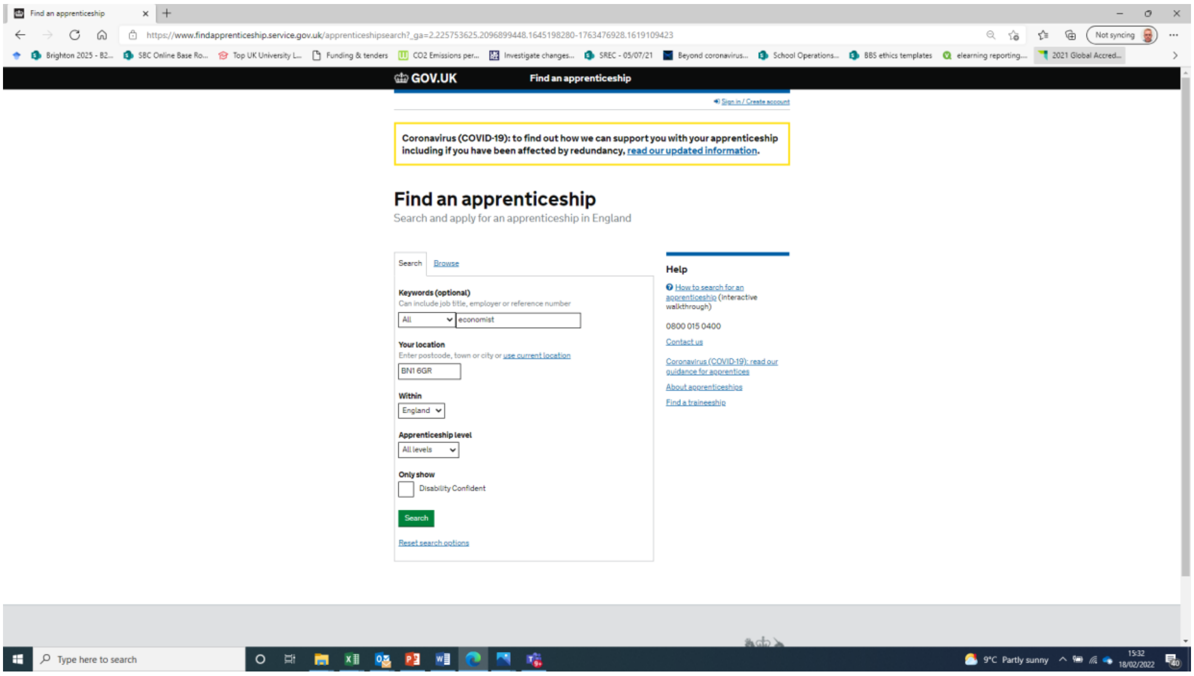
Figure A6 (cont.)/ Digital skills by SOC major groups (average frequencies, before and after the Covid-19 Pandemic*).



* Up-to/including Q1/2020 and from/including Q3/2020

Source: https://www.gov.uk/apply-apprenticeship

Figure A7. Example of an apprenticeship advert.



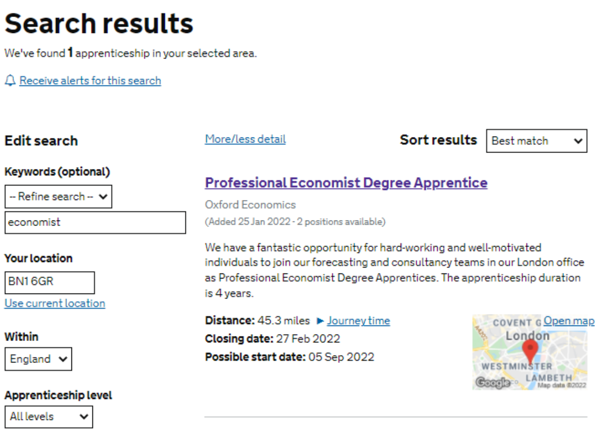


Figure A7. Example of an apprenticeship advert (cont.).

Professional Economist Degree Apprentice

Oxford Economics

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We have a fantastic opportunity for hard-working and well-motivated individuals to join our forecasting and consultancy teams in our London office as Professional Economist Degree Apprentices. The apprenticeship duration is 4 years.

This apprenticeship requires you to apply through the employer's website.

Apply now

Closing date: 27 Feb 2022

Apprenticeship summary

Annual wage
£20,000.00

Working week
Monday to Friday, 09:00 - 17:30, with a 1-hour unpaid lunch break. 23 days holiday per year.
Total hours per week: 37.50

Expected duration
4 years

Possible start date
05 Sep 2022

Date posted
25 Jan 2022

Distance
45.3 miles

Apprenticeship level
Degree
Level 6 (Degree with honours)

Reference number
VAC001811814

Positions
2 available

We have a fantastic opportunity for hard-working and well-motivated individuals to join our forecasting and consultancy teams in our London office as Professional Economist Degree Apprentices. The apprenticeship duration is 4 years.

Positions will initially be based in one of our economic forecasting or modelling and scenarios teams, but the successful candidates will be exposed to a wide variety of work in other teams over the course of their apprenticeship. You will rotate between different teams within the office during your training, giving you exposure to what the various teams do within the business.

You will begin by supporting our economists and will immediately be involved in the research we conduct for our clients. This work will provide in-depth experience in the practical use of advanced statistical and modelling software, data visualisation tools, mapping software and other quantitative analysis tools, as well as valuable and practical knowledge related to the application of economics to real world questions.

You will be supported by a mentor and our Human Resources department, as well as your line manager and team leader.

You're off the job training will be delivered, primarily at distance, by the University of Kent's School of Economics. This will be training will deliver all of the core knowledge and skills of the apprenticeship and has been designed to cover all of the nationally agreed economics subject benchmark content required for the award of a BSc Degree qualification in economics. On successful completion of the apprenticeship, you will be awarded a BSc Degree and Apprenticeship qualification.

In addition to your university studies, you will receive in-depth training at Oxford Economics. This includes report writing, communication skills, presentation skills and project management, as well as advanced Excel skills, applied econometrics and introductory programming. It is delivered through short courses, a group project and on-the-job training. This training will be integrated with your studies.

Requirements and prospects

Desired skills

- Strong quantitative skills
- Excellent written and verbal communication skills
- Knowledge of Microsoft Office packages

Personal qualities

- A good eye for detail
- A hunger to learn
- Eagerness to apply economics to address the issues that clients face

Desired qualifications

- 3 A Levels at grade B or 120 UCAS points (or equivalent)
- GCSEs (or equivalent) in maths at B/7 and English at C4

Please ensure your grades are made clear on your CV or cover letter.

Future prospects

There is the opportunity for continued employment past the apprenticeship end date.

Things to consider

If you are put forward for our Apprentice Scheme, you will be expected to attend an informal interview, which may be virtual or in person. The interview will be with the head of department and Human Resources. As part of the interview process there may be some testing on your Maths and English skills.

Oxford Economics is an equal opportunity employer that is committed to diversity and inclusion in the workplace. We prohibit discrimination and harassment of any kind based on race, colour, sex, religion, sexual orientation, national origin, disability, genetic information, pregnancy or any other protected characteristic as outlined by federal, state or local laws.

About the employer

Oxford Economics is a leader in global forecasting and applied economic analysis. Our client base includes more than 2,000 international corporations, financial institutions, governments, central banks and universities.

Headquartered in Oxford and with over 20 offices around the world, we employ 500 staff, including over 300 economists and analysts. Our best-in-class global economic and industry models and analytical tools give us an unparalleled ability to forecast external market trends and assess their economic, social and business impacts.

Employer
Oxford Economics
https://www.oxfordeconomics.com/

Address
4 Millbank
LONDON
SW1P 3JA

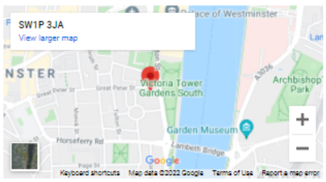

Figure A7. Example of an apprenticeship advert (cont.).

Training

Training provider
THE UNIVERSITY OF KENT

Applications for this apprenticeship are being processed by THE UNIVERSITY OF KENT

Contact
Amy Murphy 01634888949
recruitapprenticeships@kent.ac.uk

Level 6 Professional Economist apprenticeship standard, which includes:

- BSc in Economics

Apprenticeship standard
Professional economist (integrated degree)
Level 6 (Degree with honours)

Employer's Application Instructions

All applications, including CV and covering letter should be submitted to recruitment@oxfordeconomics.com.

This apprenticeship requires you to apply through the employer's website.

Apply now
Closing date: 27 Feb 2022