Digital Skills in Apprenticeships: Executive Summary

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Introduction, existing evidence and objectives of the study

Digital skills, i.e. skills for accessing, evaluating, and organising information and electronic data, have become relevant in most occupations (Ananiadou and Claro 2009). Indeed, they are vital for social inclusion generally as fulfilled lives increasingly depend on people's abilities to operate effectively in a range of digital environments – from written and verbal communication via online shopping and access to culture, resources, public services, to economic opportunities, jobs, and prosperity. Over the last few years, there has been wide agreement that the use of technology, including digital skills and their usage, "reinforce existing inequalities, as human capital carries over to the online world" (van Deursen et al. 2021). This is specifically relevant where 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 a number of frameworks have been developed conceptualising the full range of digital skills involved (Vuorikari et al., 2016, UK Digital Capabilities framework by Jisc, 2016 or the Essential Digital Skills Framework[1] used by DCMS/DfE/Lloyd), there are only a few studies on the empirical earnings effects of digital skills making use of such conceptualisations. Instead, most of the empirical estimates of earnings returns to digital skills make use of available research surveys such as the OECD's the Programme for the International Assessment of Adult Competencies (PIAAC, e.g. Falck et al., 2022). As with most of the empirical research on returns to education, this research relies on education and selective digital skills reported by the survey respondents, i.e. supply measures of these skills (e.g. Krueger, 1993; Felstead, et al. 2007, Dolton and Makepeace 2007). Less information is available for digital skills involved in specific occupations, i.e. a measure of labour demand, except for expert systems like O*NET. Finally, there is limited research on digital skills in employment accessed via apprenticeships, which represent a wide spectrum of jobs requiring mid-level skills.

Our research presented here contributes to the evidence base on the return to investment in digital skills on individual earnings and employment as well as the debate how skills and earnings opportunities can be improved with apprenticeship training (e.g. Gonzalez Vazquez, et al. 2019 or

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

Wuttke, Seifried and Niegemann 2020). The main section of the report describes the digital skills involved in jobs related to apprenticeships and provides estimates of the earnings differentials associated with digital skills. The empirical analysis is motivated by the Mincer model and regression analysis making use of new data obtained from online vacancies for apprenticeships (published between 2018 and end of 2021 on https://www.gov.uk/apply-apprenticeship).

As data from online vacancies can be obtained easily, at large scale and for very recent time periods, they are a representative source for the utilisation of digital skills in jobs involving mid-range vocational education after the Covid-19 pandemic, which introduced the much wider use of remote working practices among white collar workers, often involving digital environments. Given the very large size of the data – based on our Freedom Of Information Act (FOIA) request, we obtained data for more than 433,000 vacancies from 300,000+ job ads – they also allow to explore some detail on the skills involved.

The main empirical basis of the analysis makes use of the data from the text field of job descriptions and skills requirements included in the vacancies, which are combined to a large text corpus. In addition, we use some of the structured data included in the online vacancies, for example the hourly pay, which we created for each apprenticeship job based on various fields, as well as the sector, the level of education (intermediate, advanced, higher), related Standard Occupational Classifications (SOC), apprenticeship duration and education provider.

Using our database, we create an empirical dictionary of digital skills from the corpus applying text mining methods. This dictionary is then used to systematically describe the digital skills involved in different types of apprenticeships (by levels of education, sector, SOC, etc.) focusing on their frequencies of mentioning in vacancy adverts.

As apprenticeships have a consistent link to SOC-Codes (created by the Office for National Statistics, ONS), the main descriptive part of this report makes use of this classification. It shows that most apprenticeships are related to occupations at mid-range of skills with Level 3-5 education, such as Administrative and Secretarial (SOC 4); Skilled Trades (SOC 5); Caring, Leisure and Other Service Occupations (SOC 6). A central finding is that the inclusion of digital skills is such occupations is now widespread and in particular data skills are highly sought across occupations. We also distinguish between basic and advanced digital skills, showing much wider adoption of basic digital skills across main SOC groups.

To evidence the association of digital skills and earnings, we estimate a range of regression models explaining wage differentials by digital skills involved conditional on a range of further characteristics available, including fixed effects to control for base-level wage differentials across the full range of SOC-3 level occupations.

Based on these regression models in the Mincer tradition, we then 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.

To address the possible measurement errors of earnings and to estimate the impacts of digital skills on earnings in the medium-run, we also estimate regressions with digital skills found in our vacancy data aggregated to three-digit SOC-Level, which we then link to microdata on earnings from the Annual Survey of Hours and Earnings (ASHE) at SOC-3 level. These regressions exploit the variation of individual occupations within larger SOC groups to estimate returns to digital skills while conditioning on individual characteristics from the microdata, such as gender, age, work experience and formal level of education. In contrast to the apprenticeship vacancies, the ASHE data (based on occupations) are representative for all workers in dependent employment and thereby – at given technology – represent the life-course earnings trajectories for occupations as the individual-level regressions control for work experience and further characteristics.

In the empirical results, estimates based on ASHE result in larger earnings differentials associated with digital skills over the life course. However, a big caveat is that these "life-course earnings" differentials are related to current technology. Therefore, extrapolating this evidence is not convincing as digital skills are rapidly evolving. Hence, the main purpose of the ASHE analysis rather aims for a validation of the findings from the vacancy data and to gain some confidence whether earnings differentials estimated with the vacancy data are plausible and hold across the wider population, when work experience can be incorporated in the models to pick up life-course earnings profiles.

Project methodology

Initially, we obtained online vacancy data from the UK Government via a Freedom Of Information Act (FOIA), and after the Education and Skills Funding Agency made the data subsequently available, we downloaded the full database in December 2021. These vacancy data represent a semi-structured data format, which some fields offering structured information (working hours per week, pay, duration, the relevant Apprenticeship standard, starting date and work location) and others with unstructured text, in particular the description of the job roles and knowledge, skills and behaviours involved.

We transform the source data to quantitative research data for the whole set of apprenticeship vacancies (N=433,799 based on the 303,028 adverts) and add further characteristics such as the "Apprenticeship Standard", i.e. the legal document underpinning the required qualifications, which include further information such as level of qualification, maximum funding, expected duration and the SOC code. We also add local authority names and Travel-to-Work Areas (TTWA) using the employer postcode as the key reference and link vacancies to data from the Annual Survey of Hours and Earnings data (ASHE) at the level of three-digit SOCs and at the TTWA-level of geographies.

In order to gain information on the digital skills involved, we use the field "description", which includes the free text under "Apprenticeship summary" about the occupations aimed for with the apprenticeship, and summarise word frequencies. The outputs from this processing stage are primarily frequencies of terms, which are then used to create dictionaries to establish the number of digital skills involved in jobs assessed via apprenticeships. Such frequencies are often shown in Word Clouds, where the size of the font indicates the relative frequencies at given number of most frequent terms. Figure 1 provided an 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 thus, have been before further processing the data in order to create a dictionary.

Figure 1. 500 most frequent terms in "digital route" apprenticeships.

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

We use the word frequencies to create data-driven dictionaries, i.e. lists with key digital skills identified, to describe frequencies type of digital skills involved in different apprenticeships. This procedure is similar to other work based on apprenticeships vacancy data (e.g. Stops et al. 2021) making use of dictionaries.

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. 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.

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.

An additional complication is to understand the proficiency in digital skills used. Previous work aiming for quantitative data on digital skills established e.g. a pyramid containing self-defined concepts and keywords to differ the different levels of complexity, see Beblavý, et al. (2016). Similar to this study, 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 reflects the incorporation of digital skills at different levels of proficiency: The increasing Level of Apprenticeships represent increasing standards of knowledge, skills and competences required and allows us 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. 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.

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.

Key findings

Digital skills used in major occupational groups

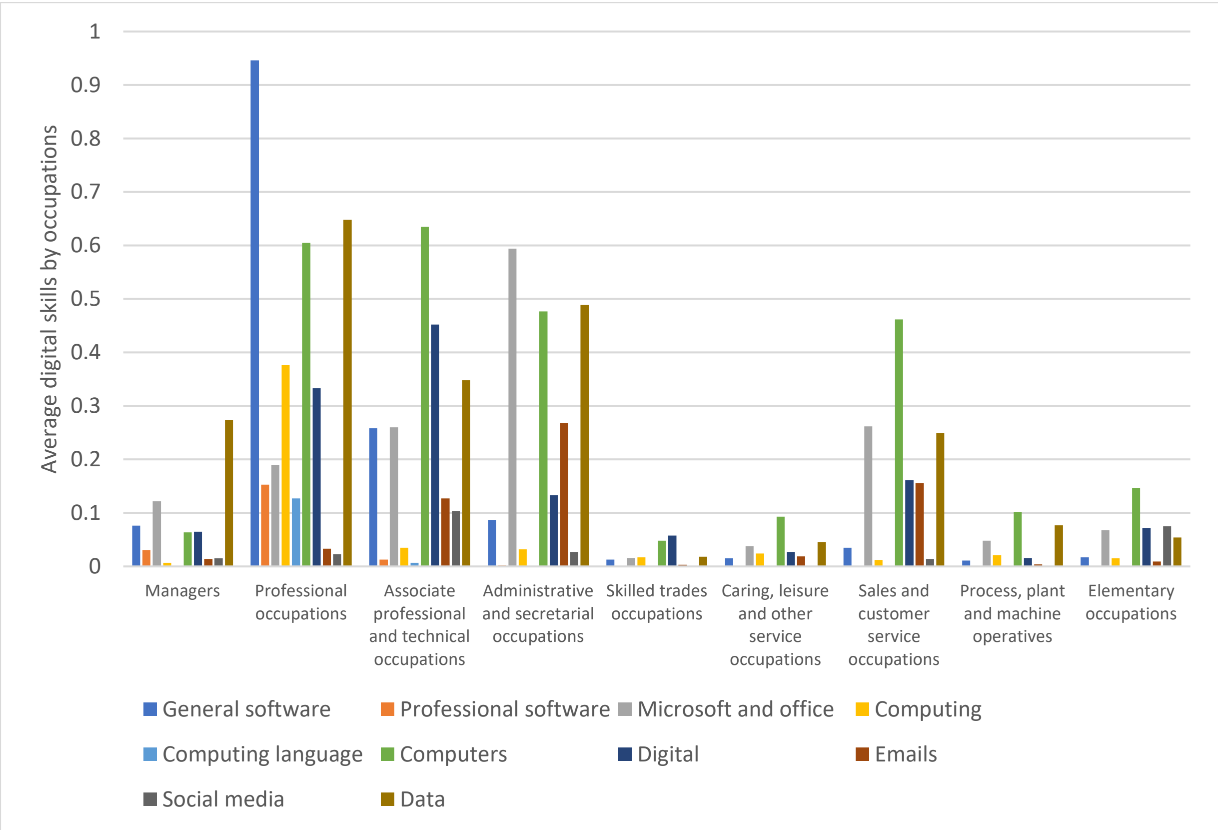
Figure 2 shows the results of digital skills required across SOC categories, i.e. the average numbers of digital skills demanded for each occupation. The main finding is that the frequencies of mentioning any of these skills from the dictionary in the text body is low, except for professional, associate professional and administrative/secretarial roles, where mostly between one in two or – for the professional roles – just about every advert shows at least one of these skills. These are fewer skills than we had expected, suggesting that many skills are assumed to be covered with the tasks outlined in the job description and do not require explicit mentioning. Where digital skills have been explicitly included, the following pattern can be described:

- 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 2. 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 digital 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.

Earnings effects of digital skills

Using earnings information from the job adverts, which largely represent an entry-level wage for the occupation aimed for with the apprenticeship, we estimate empirical 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.

Table 3 shows that the effects of digital skills are positive on hourly pay only in lower-level occupations compared to insignificant effects in higher-level occupations. Significant earnings differentials are only found among administrative, skilled trades, and elementary jobs. Based on the descriptions shown above, we found that administrative jobs have incorporated more digital skills than other SOC major group at mid-level skills. Therefore, 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. With positive and largest-size coefficients found especially for the occupations in the skilled trades, the results suggest that jobs traditionally not requiring strong ICT skills started to incorporate digital skills relative more. In the related job adverts, the skills are more explicitly shown in the job descriptions because they cannot be straightforwardly assumed from job tasks and where mentioned show significant and sizeable earnings effects.

Table 3. 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 4). The effects are strongest for vacancies trades for skilled trade apprenticeships. In contrast, basic digital skills are associated with lower wages.

Table 4. 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.

Summary of results and relevance to policy

We summarise the findings in relation to our three hypotheses:

- Hypothesis 1: 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 early career.
- On Hypothesis 2: 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: Positive earnings differentials are largely driven by more 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.

In simple words, basic level digital skills are now widely expected. The negative wage effects found here suggest that an explicit mentioning of specific basic digital skills in job ads likely corresponds to lower-level job tasks and related skills demand. 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. Low level training, such as the European Computer Driving License, might be is essential for digital inclusion, but is unlikely to result in higher wages and worker productivity. However, many apprenticeships still include such low-level education – Information and Communication Technologies (ICT) aligned to "Functional Skills" at Level 2 ("Skills for Life").

In the light of our findings, improving workforce skills for occupations requiring mid-level qualifications should involve apprenticeship training for more advanced digital skills: general and professional software, computing, and computing languages. Whilst utilisation of these skills ultimately depends on employers' need in production, an improved provision of the more advanced digital skills in education improves skills available to employers and thus allows for their utilisation to achieve higher workplace productivity and earnings.

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