# The economic impact of closing the work essential digital skills gap

Produced by Cebr

in partnership with FutureDotNow

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# Introduction

There is a widespread lack of basic digital skills and confidence among working-age adults.

For years, this issue has been largely hidden, in part due to the lack of specific economic data on the relationship between essential digital skill levels in the workforce and critical productivity and prosperity metrics.

Addressing this data gap was identified as a priority action in FutureDotNow's Roadmap[1] to close the workforce digital skills gap, published in July 2023.

In Spring 2024, a cross-sector team led by Cisco and FutureDotNow undertook a review of publicly available data to assess what information existed that explicitly linked the, then, 54% of working-age adults without the essential digital skills for work, to productivity and other key metrics. The review team identified a clear data gap; the limited data available was non-specific and out-of-date, and there were no government-owned data sources on this topic.

This report, produced by Cebr on behalf of FutureDotNow, with support from the Department for Science, Innovation and Technology, represents a first step to address this data gap.

The results are compelling. Read on to find out more.

**Navigating this report**
In addition to the detailed economic analysis on pages 12-26 you will find:



**This report has been produced by Cebr on behalf of FutureDotNow, with support from the Department for Science, Innovation and Technology.**

future .now

FutureDotNow is leading the mission to close the workforce essential digital skills gap in the UK. Established in 2019, the charity is building new understanding of this part of the UK's digital skills challenge while coordinating industry action to equip the UK labour force with the digital capability and confidence they need to thrive in work and prepare for our digital future.

You can find out more about our work, including the Workforce Digital Skills Charter and how to become a member at www.futuredotnow.uk.

1 https://futuredotnow.uk/research-and-reports/digitalskillsroadmap/

# Executive Summary

**The UK is facing an urgent challenge.**

In 2025, over half of working-age adults (52%) are unable to do the 20 basic digital tasks[2] deemed by government and industry as essential for the modern workplace. At the current pace, it could take more than 25 years to close this gap. The changing face of work due to AI and automation adds urgency to building a digitally confident and competent workforce.

This report uses robust econometric analysis to quantify the extensive economic benefits of tackling this vital part of the workforce skills gap.

### Key Findings

| THE ECONOMIC OPPORTUNITY | | | |
|---|---|---|---|
| For individuals | For the UK | | For business |
| **£897** | **£10.3 billion** | **£23.1 billion** | **£8.5 billion** |
| Average earnings uplift per full-time worker per year | Aggregate earnings uplift per year | Annual productivity gain (GVA uplift) | Annual profitability gain (GOS uplift) |

**Individuals to see higher annual earnings and improved likelihood of getting a job**

For individuals, building the 20 Essential Digital Skills for work is linked to an £897 uplift in annual earnings for an average full-time employee and an increased likelihood of getting a job.

Some groups could see even higher returns from building their digital skills than the national average, for example:

- £903 annual increase for those working in high-skilled service sectors
- £1,136 for employees of mid-sized firms (50 – 249 employees)
- £1,988 for those working in London
- £4,863 for those working in the North-West (highest wage premium)

If all currently under-skilled workers upskill, the research shows barriers to getting a job would reduce and an estimated 12,336 people could enter employment. This would create an additional £260 million in aggregate earnings per annum.

**The UK could realise £23bn in productivity gains and c.£9bn in profits every year**

Building essential digital skills does not just benefit individuals. Where higher wages stem from increased productivity driven by improved digital skills, workers produce more value per

2 2024 Lloyds Bank Consumer Digital Index. See Appendix 2 for the full list of Essential Digital Skills for Work.

hour worked. This leads to increased business output, measured in Gross Value Added (GVA)[3], and increased profitability, measured in Gross Operating Surplus (GOS).

- **Higher earnings:** If every worker currently not able to do all 20 essential digital tasks built the skills they are lacking, the economy could see an aggregate earnings uplift of £10.3 billion per annum. And higher earnings correlate to higher productivity.

- **Productivity gains:** An earnings uplift of £10.3 billion would typically correspond, through productivity effects, to an increase in UK output (GVA) of £23.1 billion. This is equivalent to c.1% of total GVA in 2022[4] or the contribution of the advertising and market research industry that year[5]. Widespread upskilling would contribute to the UK's Gross Domestic Product (GDP) for years to come.

- **Larger profits:** Increased output drives increased profitability. A £23.1 billion uplift in GVA would typically correspond to an increase in profitability (GOS) of £8.5 billion annually.

To bring this to life, a construction organisation based in the North-West employing 100 full-time workers with low digital skills could increase its annual output (GVA) by £300k and its annual profits (GOS) by £100k from all workers learning to do the 20 Work Essential Digital Skills. Arguably, a compelling case given the relative cost of the digital upskilling.

**Methodology**

The analysis is underpinned by two core econometric models:

1. A linear regression model that isolates the impact of digital skills on annual earnings, controlling for variables such as education, experience, industry, firm size, and region.

2. A logistic regression model that evaluates the role of digital skills in increasing the probability of employment. The digital capabilities of workers are assessed via a uniquely constructed Digital Skills Score (out of 100), balanced across the five pillars of skills in the Essential Digital Skills for Work framework (Communicating, Problem Solving, Handling Information, Transacting, and Being Safe Online) and the 20 specific tasks (see Appendix 2).

**What this means for business**

This report provides powerful new insight for businesses on the value they can unlock by helping people build the specific skills in the Essential Digital Skills framework.

3 Gross Value Added (GVA) is the value of output minus the value of intermediate consumption. This can be thought of as the contribution to the economy's GDP.

4 UK National Accounts Blue Book, Office for National Statistics, 2024.

5 Annual Business Survey, Office for National Statistics, 2024. The civil engineering SIC code produced an approximate GVA of 21.0 billion in 2022.

This is not about building proficiency in more technical, specialist tasks such as coding and designing algorithms. It is about helping people build the very basics. Sending an email, filling out an Excel spreadsheet, knowing how to stay safe online, or using software to log expenses or check their payslip. Skills that are increasingly essential in *any* job, no matter the field.

By prioritising targeted training for workers in the Essential Digital Skills, employers can unlock substantial gains in productivity, innovation and prosperity. And receiving that training at work is much more impactful - this report shows that employees who receive digital skills training at work perform better than those who only access training out of work.

Businesses don't need to go it alone either. There's a substantial body of support available from FutureDotNow, including tools and resources, and access to a network of peers. Launching alongside this report is the FutureDotNow calculator, an interactive model that allows an organisation to estimate the economic benefits for their organisation, based on their sector, region and organisation size.

**What this means for policy makers**

The data shows a clear national economic prize – and significant opportunities at regional and local level. The report highlights the relationship between building strong digital foundations and employability, which can open up the labour market to individuals who are currently unemployed and ensure career longevity in a digital workplace.

The Essential Digital Skills Framework is recognised as a national asset, and policy makers are encouraged to strengthen its positioning as a shared resource for businesses, civil society, and government. This includes ensuring clear ownership and that it keeps apace with technological developments.

Policy makers can also play a critical role in convening and supporting business action, including providing financial incentives for training provision. Additionally, the report underscores the importance of affordable connectivity and devices in building digital capability levels.

**Closing the Work Essential Digital Skills gap in UK workers is not a training challenge, it is a strategic economic priority. Equipping the c. 21 million workers with these skills would enable the UK to unlock substantial gains in productivity, innovation, and overall prosperity.**

**This report shows that smart, targeted investment in digital training will drive significant improvements at both the individual and national levels, laying the foundations for a more competitive and resilient economy and a modern digital society.**

# Contents

# Foreword from the National Technology Adviser: Dr Dave Smith

Department for Science, Innovation & Technology

**Bridging the Digital Divide: Preparing for the Age of AI**
It is my pleasure to have sponsored this comprehensive and important study. We can't turn on the TV today, or open a social media app, without hearing someone declaring that we stand on the brink of an AI revolution. They are right.

This will be a transformative era that promises to revolutionise industries, economies, and societies. However, this promise comes with a caveat - without a workforce equipped with basic digital skills, many will struggle to keep pace.

The findings of this report underscore the urgency of addressing the digital skills gap. A staggering 52% of the UK workforce lack at least one of the 20 essential digital skills, and 6% lack all of them. We cannot afford for a generation of people in the UK workforce to be left behind.

Who needs to act to change this state - us as individuals of course, and also, above all, businesses. Why businesses? Because, in addition to being part of their social responsibility, it is in the self-interest of businesses, as this report clearly shows. Investing in the digital skills of your people directly correlates with your profitability.

The data provides a detailed analysis of the current state of digital skills within the workforce, quantifies the economic impact of closing the digital skills gap which exists, and offers actionable insights for individuals and, most of all, for businesses.

Digital skills are not just a prerequisite for engaging with AI; they are fundamental to securing good quality jobs in the modern economy. As the report highlights, roles requiring digital proficiency are increasingly becoming the norm, with employers prioritising candidates who can navigate and leverage digital tools. This trend is set to continue, making digital literacy a key determinant of an individual's success.

The study is a call to action for businesses to invest in digital upskilling initiatives, which will later ensure that our workforce is digitally-equipped to thrive in the age of AI.

Although businesses will play a central role, Government-private sector partnerships to address this issue will also be valuable. In my role as National Technology Adviser, I have also led a Review of Technology Adoption in the UK as an input to the Industrial Strategy.

Lack of workforce digital skills is one of the primary barriers preventing technology adoption by businesses in the UK, which is itself believed to be a key contributor to the weak productivity growth which has plagued the UK since the financial crisis. Working together with industry to address the workforce digital skills gap is therefore critical to unlocking growth in the UK.

I commend FutureDotNow for their dedication to this vital issue and to gathering evidence. Together, we can bridge the digital skills gap and unlock the full potential of both our people and AI for the benefit of all.

# 1. FutureDotNow perspective: What the findings mean for business

Digital transformation and skills challenges are high on the business agenda. However, the core digital capability of workers across the UK and the relationship this has to growth and business resilience has been largely hidden in plain sight.

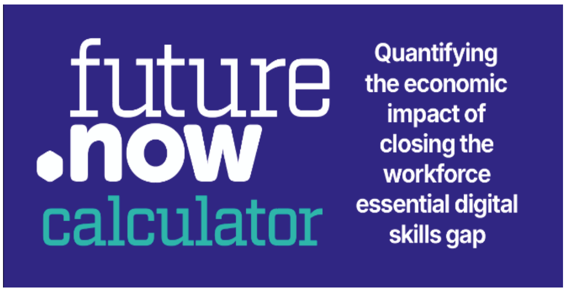
Since inception, FutureDotNow has championed the importance of equipping workers with basic digital capability and confidence. We've always been confident that investing in these very basic skills would deliver returns to business, but there was a lack of hard, economic, evidence that proved it. Until now.

This report, commissioned by FutureDotNow with support from the Department for Science, Innovation and Technology, starts the process to change that.

The Centre for Economic and Business Research has authoritatively quantified the benefits of improved essential digital skills on individuals, on business performance, and on the economy.

And it's good news. The research shows that equipping workers with the 20 Essential Digital Skills for Work can deliver increased productivity - an additional £23.1 billion in Gross Value Added (GVA) per year - and increased profitability - nearly £9 billion in Gross Operating Surplus (GOS) per year. And these gains are not just a one-off; once a worker becomes more productive, they stay more productive, these returns would continue year on year.

## 1.1 The FutureDotNow Calculator




Alongside the report, FutureDotNow members have access to the FutureDotNow calculator**,** an interactive model that allows an organisation to view the benefits at a local level. By selecting their sector, region and organisation size, the model will provide an estimate on the productivity and profitability gains the organisation could enjoy.

Two worked examples are shown overleaf: one for a mid-sized construction firm in the North-West of England, and one for a large retailer in London.

| FutureDotNow calculator | | |
|---|---|---|
| *Sector* | **Construction** | |
| *Region* | **North-West** | |
| *Size* | **100 full-time employees** | |
| ***Benefits*** | ***Per upskilled worker*** | ***Total for all upskilled workers*** |
| Uplift to annual output (GVA) | £2,961 | £296,078 |
| Uplift to annual profits (GOS) | £1,083 | £108,284 |

| FutureDotNow calculator | | |
|---|---|---|
| *Sector* | **Retail** | |
| *Region* | **London** | |
| *Size* | **2000 full-time employees** | |
| ***Benefits*** | ***Per upskilled worker*** | ***Total for all upskilled workers*** |
| Uplift to annual output (GVA) | £1,478 | £2,955,451 |
| Uplift to annual profits (GOS) | £540 | £1,080,889 |

To become a member of FutureDotNow and gain access to the calculator, visit futuredotnow.uk/get-involved/

**Opportunity for business**

With over half of working-age adults - c. 21 million people[6]- currently digitally under-powered, there is a real opportunity for business to take concerted and deliberate action.

The Essential Digital Skills Framework provides specificity on the digital basics; the 20 digital tasks government and industry agree are essential in the modern workplace. Basic skills, such as securely accessing payslips, managing data safely online, or using productivity tools; all of which are critical building blocks for individuals to be digitally confident and able to respond to jobs and working life that are being transformed by AI and automation.

Armed with this knowledge, businesses of all shapes and sizes can normalise this basic digital upskilling and help people build solid digital foundations.

Insights from FutureDotNow member companies show that there are many ways to help workers build the essential digital skills for work and that it doesn't require bespoke expensive training programmes. But it does require intent and targeted action. And, of course, investments need to deliver a return. This report shows that is the case.
This report also shows that employees who receive digital skills training at work perform better than those who only access training outside of work.

**We encourage employers to prioritise digital skills training for workers, supporting every employee to equip themselves with the essential digital skills for work.**

6 2024 Consumer Digital Index, Lloyds, 2024: https://www.lloydsbank.com/assets/media/pdfs/banking_with_us/whats-happening/lb-consumer-digital-index-2024-report.pdf

There's a substantial body of support available from FutureDotNow, including tools and resources and access to a network of peers. Employers don't need to go it alone. To become a member or find out more, visit futuredotnow.uk/get-involved/

**Opportunity for policy makers**

This is also an important report for policymakers. The data shows a clear national economic prize – and significant opportunities at regional and local level.

It also points to the relationship between helping people build strong digital foundations and employability - opening up the labour market to those who may be currently unemployed, as well as helping ensure career longevity in a changing digital workplace.

The Essential Digital Skills Framework is a national asset providing specificity in a complex skills landscape. The importance of cross-governmental sponsorship for the framework has recently been recognised by the Government in their Digital Inclusion Action Plan[7].

**Policy makers can further strengthen the positioning of the framework as a common asset for use by business, civil society and policy makers. This includes ensuring clear ownership of the framework and that it keeps pace with technological developments.**

Of course, policy makers can also play a critical key role in convening and supporting business action, including providing financial incentives to support the cost of training provision.

It is also worth noting that the report also underlines the importance of not looking at skills in isolation; the report found affordable connectivity and devices are key for individuals when it comes to building digital capability levels. This joined up relationship is already recognised by policy makers but cannot be under-estimated.

**This is the first report looking specifically at the economic impact of essential digital skill levels in working age adults.**

**It is a critical step in the collaborative effort between business and government to unlock the potential of millions of working age adults across the UK and unleash the economic benefits that come from a modern digital society.**

**We hope you find the content inspiring and useful.**

7 Digital Inclusion Action Plan: First Steps - GOV.UK: https://www.gov.uk/government/publications/digital-inclusion-action-plan-first-steps/digital-inclusion-action-plan-first-steps

# Economic analysis

Prepared by Cebr
on behalf of FutureDotNow


Authorship and acknowledgements
This report has been produced by Cebr, an independent economics and business research consultancy established in 1992. The views expressed herein are those of the authors only and are based upon independent research by them.
The report does not necessarily reflect the views of FutureDotNow. London, March 2025.

# 2. Economic impact of closing the essential digital skills gap

We present below the results of the two econometric models prepared for this report – the earnings and employment models – which quantify the benefits of improved essential digital skills both at an individual level and across the wider economy. For each, we provide a short discussion of our model results and trends observed in the survey data and then extrapolate our findings to the wider economy. Preceding the results is a short discussion on the background to this research and the digital skills gap.

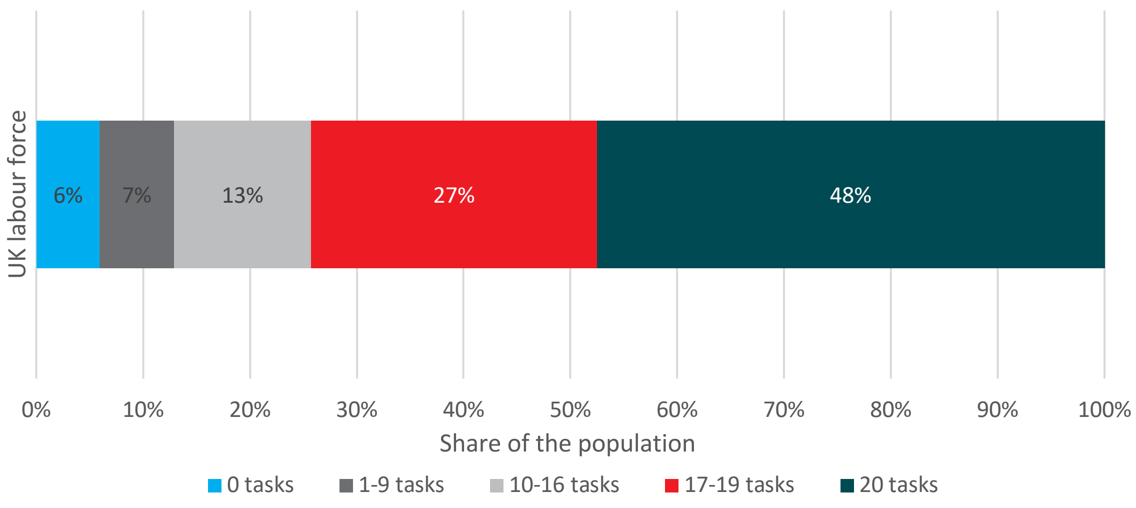
Detailed methodological discussion, as well as model specifications and regression statistics, are included in the Technical Appendix.

## 2.1 The digital skills gap

It is well established that a large proportion of the UK's population is missing the Essential Digital Skills for Work. These skills, which range from finding information online to communicating with colleagues virtually, do not represent advanced digital proficiency needed in the workplace, but rather the minimum set of skills which a person needs to safely participate in increasingly digital work environments.

Lloyds Bank has, for the past nine years, surveyed individuals on their level of digital skills and has consistently found a sizeable skills gap between lower and higher scorers. Figure 1 presents their findings on the number of Work Essential Digital Skills people in the UK labour force could carry out in 2024.

Figure 1: Number of tasks people can do independently across the UK labour force, 2024




*Source: Lloyds Bank*[8]

8 2024 Consumer Digital Index, Lloyds, 2024: https://www.lloydsbank.com/assets/media/pdfs/banking_with_us/whats-happening/lb-consumer-digital-index-2024-report.pdf

As seen above, 52% of the UK labour force is missing basic skills around digital safety and productivity. At the lowest end of this, 6% of people are not able to do any of the skills deemed necessary for engagement in the modern workplace, with a further 7% only being able to do fewer than 10 skills.

We set out to test the hypothesis that those lacking digital skills also experience lower average earnings and lower likelihood of employment. This hypothesis is informed by a wealth of evidence on the increasing importance of digital skills in the UK labour market. Research commissioned by the Department of Culture, Media, and Sport, for instance, found that digital skills are essential entry requirements for two-thirds of UK occupations, accounting for 82% of online job vacancies[9]. They also found that roles requiring digital skills paid 29% over roles that did not, with higher wages most likely reflecting higher average worker productivity.

In the analysis below, we score survey respondents' level of digital skills out of 100, based on how many Work Essential Digital Skills tasks they can carry out. We therefore refer to their Digital Skills Score and explore how this is related to their labour market outcomes.

## 2.2 Impact of closing the skills gap on earnings

This subsection describes the results obtained from our earnings regression model, which aims to test whether individuals with stronger digital skills tend to earn higher annual salaries. The model seeks to isolate the independent effect of digital skills on earnings, controlling for other relevant factors. We then present the results of an assumption-based extrapolation exercise. These should be taken as illustrative, describing the potential upper-bound economic impact associated with increased digital skills across the labour force.

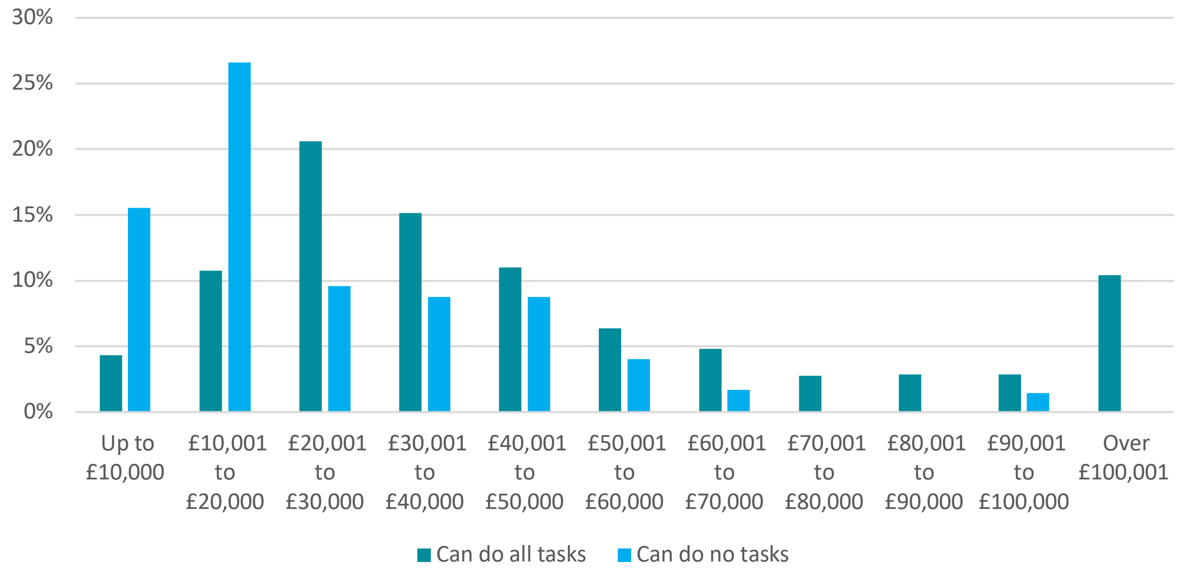
### Impact of improved Work Essential Digital Skills at the individual level

Our econometric earnings model, detailed in the Technical Appendix, finds that a one-point increase in an individual's Digital Skills Score is associated with a **0.22% increase in their annual earnings, on average**. Given the distribution of digital skills in our sample, this suggests that a full-time worker in the lowest quartile of digital skills who improves their Digital Skills Score to match the median worker could expect to see their salary increase by approximately **4.1%**, or by **£840 annually.**

In order to understand the motivation behind our econometric model, we present the distribution of annual earnings in our survey sample in Figure 2, segmented by the number of Work Essential Digital Skills tasks respondents said they could do independently. Specifically, we show the difference in earnings between those who could do all 20 tasks and those who could do none.

9 No longer optional: Employer demand for Digital Skills, Department for Media, Culture, and Sport, June 2019

Figure 2: Distribution of annual earnings by respondents' level of digital skills




*Source: Opinium, Cebr analysis*

From the raw data and before running any further analysis, we observe already a positive relationship between digital skills and annual earnings. Beyond this correlation, our econometric model investigates whether this positive relationship is also statistically significant. In other words, by controlling for factors which are likely to also be correlated with earnings (such as education, age, and labour market experience), we isolate the impact of digital skills on salary.

Indeed, our econometric model found a positive and statistically significant relationship between the number of digital skills an individual could carry out and their salary. As stated, for the average individual in our sample, each point they improve their Digital Skills Score by is associated with a 0.22% increase in their annual earnings.

Beyond this average effect, we also explored differences across key subgroups. We investigated whether individuals belonging to certain subgroups were likely to see larger or smaller returns to investing in their Work Essential Digital Skills than the average employee.

Table 1, overleaf, presents the subgroups in which improving digital skills was associated with a statistically significant change in salary. The subgroups we tested were industry, English region and UK nation, and organisation size. [10]

10 Subgroup analysis was conducted by dividing the survey data into corresponding subsets. In the regional analysis, except for Northern Ireland and Wales which both had sample sizes around 40, the rest of regions had sample sizes above 50. Industries were aggregated into larger groups in order to obtain sample sizes above 50. More detail included in the Technical Appendix.

Table 1: Uplift to individual full-time annual earnings in different subgroups associated with improved digital skills

| Group | Wage premium associated with a 1-point increase in the Digital Skills Score | Average skills gap between 25th quartile and top scorers (100) on Digital Skill Score | Average uplift to individual annual earnings (learning to do all 20 tasks) |
|---|---|---|---|
| Whole Sample | +0.22% | 21 | £897 |
| Mid-sized firms[11] | +0.26% | 12 | £1,136 |
| High-skilled services[12] | +0.55% | 5 | £903 |
| London | +0.50% | 18 | £1,988 |
| South West | +0.65% | 18 | £3,210 |
| North West | +0.78% | 23 | £4,863 |

*Source: ONS, Cebr analysis*

Table 1 provides targeted insight into which employees in the economy could see the largest returns from investment in digital skills, as well as the monetary value of said returns. We observed that **an average full-time worker in the lowest quartile of our sample could increase their salary by £897 if they learned to do all 20 Work Essential Digital Skills tasks**. Employees in the North-West of England, in particular, might see the largest uplift to their salary from increased digital skills, with a 1-point increase in their Digital Skills Score being associated with a 0.78% increase in their annual earnings, 0.56 percentage points above the increase in salary expected by the average worker.

For the rest of industries, firm sizes, and regions not included in Table 1, we did not find a statistically significant difference between their wage premium and that of the whole sample. Neither did we find a notable difference for employees of different demographic groups.

While the wage premium was also high for workers in high-skilled services, lower scorers in this industry who learnt to do all 20 tasks would increase their absolute salary by less than, for instance, workers in London, despite the latter seeing a lower wage premium.[13] This is due to the baseline skill level of employees in high-skilled services already being considerably above that of the average worker, reducing the gap between lower and higher scorers to 5 points on our Digital Skills Score.

11 Organisation size is defined by number of employees and categorised as follows: Micro firms 0-9 employees, small firms 10-49 employees, mid-sized firms 50-249 employees, large firms 250+.

12 High-skilled services refers to jobs in finance, professional services, and ICT, combined in order to obtain a sample size above 50.

13 Our wage premium findings for individuals in high-skilled services could spark reverse causality (or endogeneity) concerns, as those in this industry might have more digital skills because of their job position and associated higher salary. In order to explore this possibility, we ran a model with instruments included in the Technical Appendix, and observed a lack of endogeneity between our dependent variable (salaries) and our independent variable (digital skills).

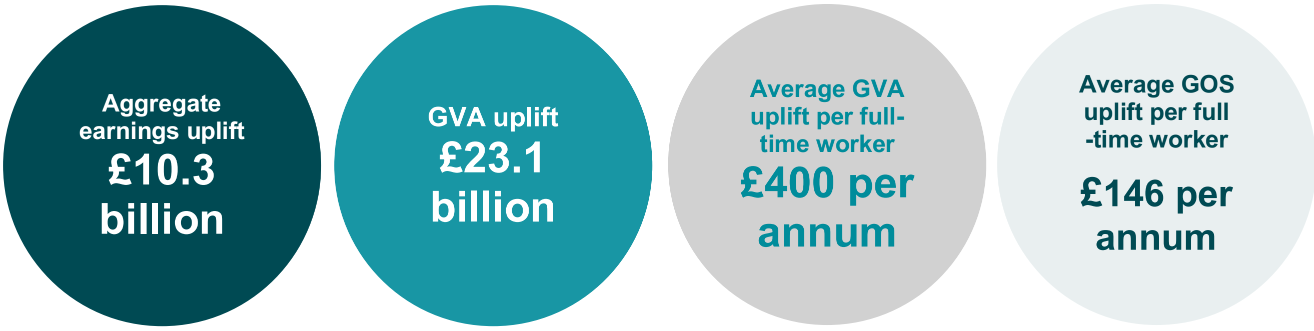
**Wider economic impact**

In order to extrapolate our regression findings to the wider economy and provide indicative results on the potential magnitude of economic impacts associated with increased digital skills, we evaluate a hypothetical scenario. This is that in which everyone in the workforce is able to do all 20 Work Essential Digital Skills.[14]

The main drivers behind the results provided below, therefore, are the outputs from our regression analysis, a series of reasonable assumptions relating to earnings and their wider impact on GDP, and the digital skills gap between the lower and higher scorers in our sample.

If every worker who is currently not able to do all 20 digital tasks were to learn the Work Essential Digital Skills they are lacking, the economy could see an **aggregate uplift to earnings of £10.3 billion**.[15]

Figure 3: Wider impact associated with everyone in the workforce learning to do all 20 Work Essential Digital Skills




In estimating the impact of this earnings uplift on the wider economy, we assume that upskilled workers would earn higher salaries because they would be more productive.[16] As well as enjoying improved productivity in their current roles, it is also likely that upskilled workers would be better placed to move horizontally to better remunerated jobs in different industries, or vertically within their own organisation or sector. Our estimates, therefore, are also dependent on the labour market being flexible enough to allow upskilled workers who wish to change into more productive positions to do so.

If these higher wages are stemming from increased productivity, i.e. workers are producing more value per hour worked, then this would also lead to increased business output, measured in Gross Value Added (GVA)[17] which approximates GDP. We estimate that an uplift to

14 We do not, however, consider whether the economy has the capacity to offer training for all workers at this scale.

15 We offer here a conservative estimate, applying our regression coefficient to the average lower quartile annual salary for full-time and part-time workers, for 2024.

16 This assumption entails other assumptions, such as productivity increases being immediately met with wage increases, and the labour market being able to absorb widespread salary increases. Additionally, we do not consider general equilibrium effects that might occur from a widespread improvement in digital skills such as competition for salaries or wage adjustments.

17 Gross Value Added (GVA) is the value of output minus the value of intermediate consumption. This can be thought of as the contribution to the economy's GDP.

earnings of £10.3 billion would typically correspond, through productivity effects, to an increase in **GVA of £23.1 billion.** To put this figure into perspective, this amounts to approximately 1.02% of total GVA in 2022[18], and is equivalent to the whole contribution of the advertising and market research industry that year[19]. Additionally, **we'd expect annual GVA-per-worker to increase by £208 per part-time worker and £400 per full-time worker**. Whether these effects manifest, further, depends ultimately on businesses' reaction to an upskilled labour force. Investment choices made by business on job creation and productivity-enhancing activities are decisive in turning upskilling into sustained economic growth.

We also estimate the increased business profitability associated with the increase in GVA above. We do so by estimating the impact on Gross Operating Surplus (GOS), which approximates the profits on production obtained by businesses once all expenses, including employee compensation and taxes, have been paid[20]. It is one of the key components of GVA and represents the portion of revenue obtained from increased output that, following a productivity shock, would be distributed to business.[21] In this hypothetical scenario, **total GOS** could see an increase of **£8.5 billion**. Correspondingly**, GOS per full-time worker would be raised by an average of £146** and **by an average of £137 per part-time worker**. A business employing, for instance, 50 full-time workers with low digital skills could increase its GOS by £7,300 per annum from all workers learning to do the 20 Work Essential Digital Skills.

Beyond this hypothetical case, our methodology allows us to estimate a range of scenarios, setting the number of digital skills gained by the workforce at different levels and estimating the corresponding economic impacts. For instance, **in a different scenario in which everyone below the median was to move to the median skill level (19 tasks**), we estimate that the earnings uplift would be of **£9.7 billion**. Consequently, **£21.7 billion** could be added to the UK's GVA, corresponding to an increase of **£375** in GVA per full-time worker per annum. Of this increase in output, we'd estimate that **£7.9 billion** would be enjoyed as Gross Operating Surplus.[22]

## 2.3 Impact of closing the skills gap on employment

This subsection describes the results obtained from our logistic regression model, which aims to test whether those with more digital skills are more likely to be in employment because of their digital aptitudes. By applying our findings to the population of unemployed people in the UK in 2024, we estimate the uplift in employment that could result from improved digital skills.

18 UK National Accounts Blue Book, Office for National Statistics, 2024.

19 Annual Business Survey, Office for National Statistics, 2024. The civil engineering SIC code produced an approximate GVA of 21.0 billion in 2022.

20 GOS does not exactly measure company profits, since only a subset of total costs is subtracted from gross output to calculate GOS, but it is the best available proxy.

21 We assume here that the ratio of GVA-GOS would remain stable, that is, that revenue from production would be redistributed to workers and to business in a way proportional to the current distribution of revenue.

22 This alternative scenario where every low scorer moves up to the median further implies that the impact of everyone moving from 19 to 20 tasks is of, in the case of earnings, of £600 million. The interpretation of this estimate is discussed in the Technical Appendix.

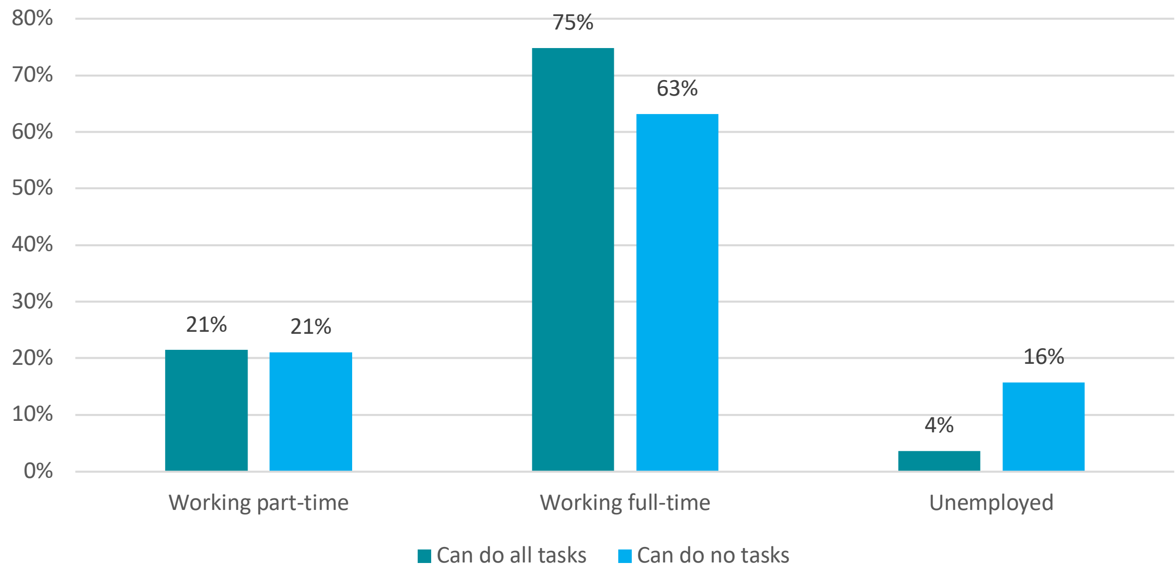
This uplift, further, contributes to earnings and GVA, our estimates of which are also included below.

**Impact of improved Work Essential Digital Skills at the individual level**

Our employment model, set out in full in the Technical Appendix, found that, on average, a 1-point increase in a respondent's Digital Skill Score was associated with **a 0.21% increase in the likelihood of them being employed**. This result is driven by the difference in the average level of digital skills between people who are unemployed and people in employment: while the former scored an average of 67.7 out of 100 in our digital skills index, the latter scored an average of 81.5.

As with earnings, the positive relationship between employment and digital skills was apparent from the raw survey data. Figure 4 below illustrates this relationship.

Figure 4: Distribution of digital skills by working status[23]




*Source: Opinium, Cebr analysis*

We observe that, whereas only 4% of those in the labour force who could do all 20 tasks were unemployed, the proportion raised to 16% for those who could do none of the Work Essential Digital Skills tasks. Given that the unemployment rate in the UK stood at 4.3% in December of 2024[24], we can see that unemployment was considerably overrepresented within the group of respondents who could do none of the 20 Work Essential Digital Skills tasks. In order to test whether this relationship is statistically significant, we used a logistic regression model which controlled for factors like years of experience in the labour force, education, disability status, amongst others, and found a statistically significant relationship between digital skills and employment.[25]

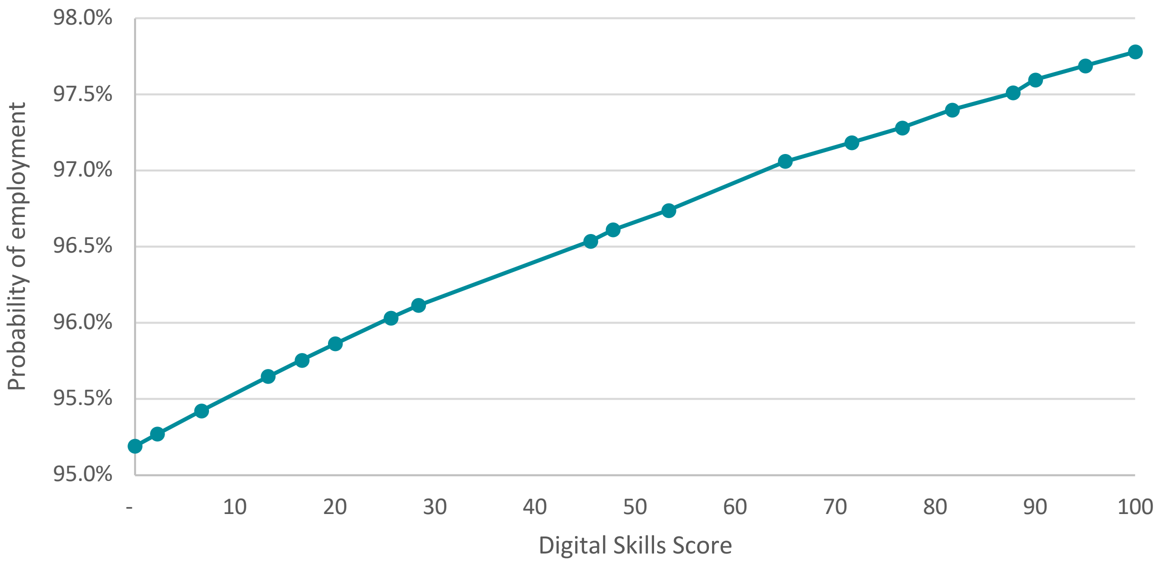
23 This graph represents only responses of those within the labour force, and it should be noted that the group of the labour force which can do no tasks has a low sample size of 38.

24 Employment in the UK: December 2024, Office for National Statistics, December 2024

25 Although the sample size of unemployed people in our data was large enough to run our logit regression on the whole labour force, it was not large enough to disaggregate further and do subset analysis. Subset analysis, therefore, is not included here, not because we don't find statistically significant effects, but because we haven't been able to test it.

A key finding from our employment model was that the impact digital skills have on probability of employment varies depending on a respondent's initial level of digital skilfulness. **The fewer digital tasks a person can do, the larger the impact improving their skills will have on their labour market outcomes**. In other words, we found diminishing marginal returns to investment in digital skills. Figure 5 visually illustrates this relationship.

Figure 5: Relationship between digital skills and likelihood of employment[26]




*Source: Opinium, Cebr analysis*

As can be seen above, probability of employment increases with digital skills, but the magnitude of the increase diminishes as a respondent's initial level of skills rises. In going from a score of 55 to a score of 70, for instance, an individual would increase their probability of employment by an average 0.41 percentage points, whereas in going from 70 to 85, they would do so by an average 0.28 percentage points.

If the average unemployed person, with a score of approximately 68, learnt to do all 20 Work Essential Digital Skills they could increase their likelihood of employment by an average 0.71 percentage points.

### Wider economic impact

If everyone who is unemployed and unable to do all 20 tasks learnt the Work Essential Digital Skills they were lacking, **12,336 people could enter employment.** This would constitute about **0.8%** of the number of unemployed people in the UK as of March of 2025[27].

26 It is worth noting that the baseline likelihood of employment is considerably high (slightly above 95% for those with no digital skills) this estimate is driven by the large number of people in employment in both our sample and the wider UK population. As of November 2024, the UK's unemployment rate was of 4.4% meaning, as for our sample, that any person in the labour force is considerably more likely to be employed than to not be. The upshot of the graph presented here is to illustrated that this probability of being employed increases further as digital skills increases.

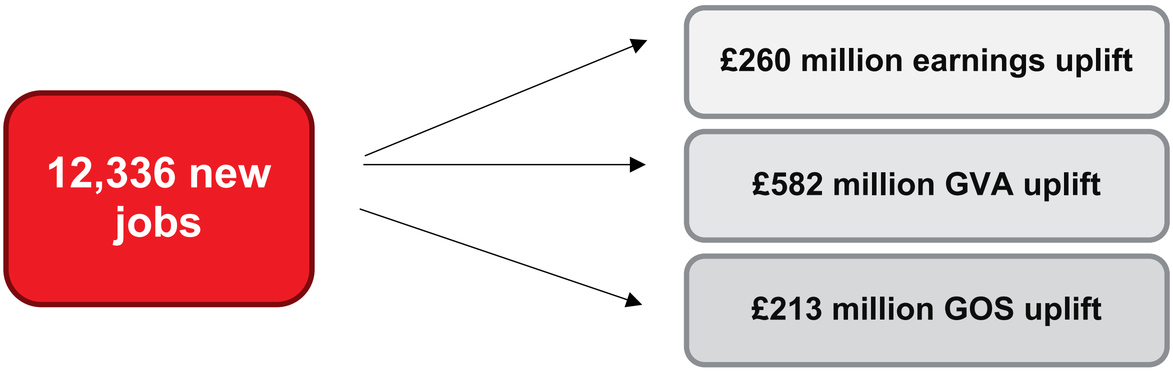
27 A01: Summary of labour market statistics, Office for National Statistics, 20 March 2025: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/summaryoflabourmarketstatistics

We would expect to see, in this case, that unemployed people previously unable to join the workforce could find reduced barriers to employment following upskilling. It could be the case, both that they are able to access jobs they were previously unqualified for, and that upskilling makes them more productive and therefore more desirable hires.
For this increased employment to manifest, certain conditions would have to be present in the economy, such as a labour market flexible enough to absorb new workers and to do so in roles which utilise their newly learnt digital skills.

As more people enter the labour force, total earnings would also increase, estimated in this case to rise by £260 million[28]. Increased earnings, as above, would probably reflect the increased productive potential of unemployed people following upskilling opportunities.
As described in the case of earnings, therefore, we would expect increased productivity to manifest in the form of improved efficiency and an uplift to total output, with GVA estimated to raise by £582 million if all lower scorers who are unemployed were to learn all 20 tasks.

Consequently, GOS, which estimates business profit, could raise by £213 million as increased revenues from an upwards shock to GVA are distributed, in part, in the form of profit to business. In actuality, whether increased revenue following an uplift in output is redistributed primarily to business or to workers will depend on labour market conditions at the time of upskilling, such as the rate of unemployment in the economy and labour market tightness.

Figure 6: Employment impact associated with everyone in the workforce learning to do all 20 Work Essential Digital Skills




As with our earnings model, we are here able to consider different scenarios as well as that of everyone learning to do all 20 Work Essential Digital Skills tasks. In the case, discussed above, that **everyone below the median skill level moved up to it** (i.e. learnt 19 Work Essential Digital Skills tasks), **9,631 jobs could be added to the economy.** This increase in employment would correspond to a £203 million uplift in earnings, £454 million uplift in GVA, and £166 million uplift in GOS.[29]

28 We make here a conservative estimate, as we assume that people entering the labour market do so at the lowest quartile average salary. We don't consider here any effects that increased employment might have on wages across the labour force.

29 Further discussion of how these estimates relate to those presented for the case where everyone learns all 20 skills is included in the Technical Appendix.

# 3. The role of business and policymakers

The previous section outlines the gains to the entire economy that could be expected from widespread digital upskilling of the UK's labour force. This section presents evidence on two routes through which business and policymakers may help to bring such upskilling along.

We first present evidence from our survey sample on the positive relationship between employer-provided training and digital skills. Those respondents who had received digital skills training from their current or a past employer had, on average, higher digital skills than those who hadn't.

We then discuss the relationship between digital skills and access to digital tools. From the survey, we observed too that a large share of respondents, whether digitally skilled or not, struggled with reliably accessing devices and digital connection.

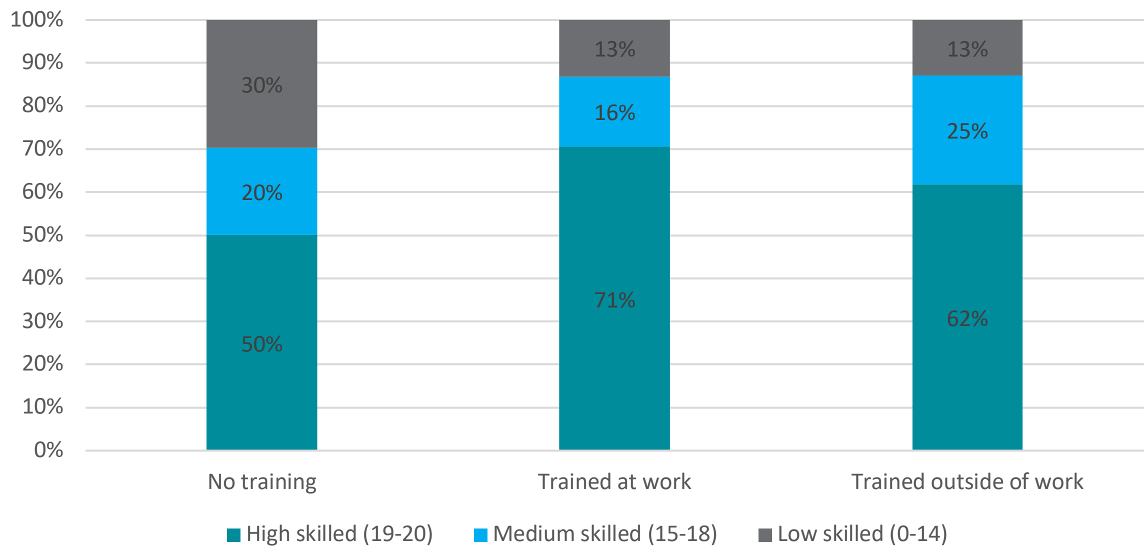
Although the findings presented in this section are only observed from our survey sample and haven't been tested through further econometric modelling, correlations discussed below still provide useful insights into where efforts aimed towards upskilling may be best concentrated.

## 3.1 Employer-provided training and digital skills

In our survey sample, those **respondents who had received digital skills training at work**, whether from their current or from a previous employer, **were on average more digitally skilled than those who had received training outside of work or who had never received training at all**.

Figure 7 below presents the share of people at each skill level who had received training or not[30].

Figure 7: Distribution of digital skills by training received, 2024




*Source: Opinium, Cebr analysis*

30 Underlying data has been weighted according to the weighting process described above.

We observe a clear correlation between receiving formal digital skills training at work and being digitally skilled. While 71% of those who were trained at work were highly skilled (i.e. could do 19 or 20 tasks), the share went down to 62% for those who had received formal training outside of the workplace, and down further to 50% for those who had received no training at all.

Of particular interest here is the difference in average digital skills between those who had received training within and outside the workplace. While still outperforming those who had never received training, employees who had only received training outside of the workplace were more likely to be medium skilled (i.e. able to carry out 15-18 tasks) than those trained by their employers, who were more likely to be high skilled.

This is most likely due to training programmes in the workplace focusing more explicitly on the essential skills required for work than those provided elsewhere. Employer-provided training, therefore, could be key in bringing employees up to 19 or 20 digital tasks, and hence in bringing about the widespread economic impact estimated in Section 2.2.

While it is possible that the offer of training is taken up by people who are already more digitally skilled and therefore confident or motivated enough to further develop their skills, this factor would still not explain why those trained within the workplace have more Work Essential Digital Skills than those trained outside of it.

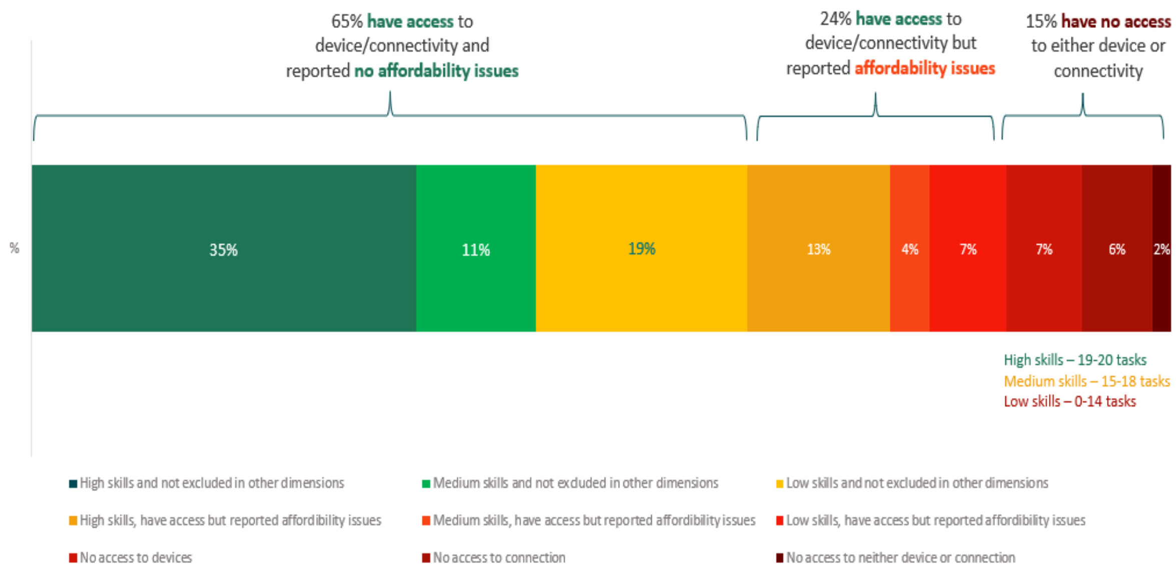
Respondents within our survey, additionally, were also asked what would motivate them to build their Work Essential Digital Skills. Around a quarter of them (26%) said that incentive schemes in the workplace would motivate them to learn new skills, with 19% citing receiving training and support from their employer as another key motivator. As well as providing training which is likely to be more relevant to the digital skills needed by employees, employers could also be key in motivating individual workers to invest in their own Work Essential Digital Skills. Business, therefore, could be central to the digital upskilling of the UK labour force, while also benefiting from the increased productivity brought about by said upskilling, as discussed in Section 2.2.

## 3.2 Access to digital tools and digital skills

A large share of respondents in our survey, whether high, mid, or low skilled, reported a lack of access to digital devices and connectivity, or affordability issues around these.

Figure 8 summarises the relationship between three variables: digital skill level, access to digital tools, and affordability of the latter. Specifically, we present novel evidence on the relationship between being digitally excluded because of a lack of digital tools and lacking digital skills.

Figure 8: Distribution of digital skills by access to digital tools and affordability




*Source: Opinium, Cebr analysis*

As can be seen above, 65% of respondents reported having access to devices/connectivity and no affordability issues, in contrast with 35% who did report either lack of access to digital tools or affordability issues. Of those who reported affordability issues but who did have access to digital tools, 54% were highly skilled, while the rest were either mid or low skilled. Those who had no access to either a device nor connectivity were equally likely to be high, mid, or low skilled.

The upshot from these survey findings is that, while we have illustrated the impact that upskilling employees could have on the UK's economy, effective upskilling will also require uncompromised access to digital tools.

In particular, the ability to look for jobs online, to interview virtually, and to work from home will, amongst others, partly inform whether those with newly developed digital skills are able to move to more productive positions or to become employed where previously unemployed. This flexibility is a key assumption underlying our economic estimates and is in great part facilitated by having stable access to connectivity and devices.

Improved access to digital tools, therefore, will have to be an effort in tandem with that of widespread upskilling, and one which would welcome attention from policymakers in the space.

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# Appendix 1
# The Workforce Digital Skills Gap

Validated by industry and government, the Essential Digital Skills Framework sets out 20 digital tasks required for work.
These are not advanced tech skills. They include tasks like accessing an online payslip, using key tools like Google Docs and Microsoft Teams to collaborate with colleagues and be more productive, and some of the basics of online security.

**52% of the UK labour force (c.21 million adults) cannot do all 20 Work tasks found in the Essential Digital Skills Framework.**
**c.2.3 million cannot complete any of the 20 Work tasks (6%).**

The three tasks most missing in the labour force:

1. Use productivity tools – 29% of workers cannot complete
2. Set privacy settings – 23% of workers cannot complete
3. Access online salary information – 22% of workers cannot complete

There are communities in which the gap is more pronounced. Not able to complete all 20 tasks are:

- 65% of part-time workers
- 65% in the construction sector
- 63% of older workers
- 62% of those with an impairment

And gap within groups often assumed to be 'high performers'. Not able to complete all 20 tasks are:

- c.1 in 5 tech sector workers (20%)
- c.1 in 3 workers earning over £75,000 p/a (32%)
- c.1 in 2 people with a degree /Masters/PhD (43%)
- c.1 in 2 18- to 24-year-olds (48%)

For more information on essential digital skills levels in the UK workforce, visit the FutureDotNow website: futuredotnow.uk/about-us/the-essential-digital-skills-gap/

# Appendix 2
# The Essential Digital Skills Framework

The Essential Digital Skills Framework reflects the range of skills people need to safely benefit from, participate in and contribute to the digital world of today and tomorrow, in life and at work.

It outlines five key skills and the digital tasks that people should be able to complete to demonstrate each skill. The framework is underpinned by the foundation skills an individual needs to access technology at the most basic level (e.g., turning a device on, using a mouse etc).


## The 20 essential work tasks

Across five skills areas in the Essential Digital Skills Framework, 20 tasks are considered essential for a modern workplace.

**Handling content and information** (two work tasks)

1. Follow my organisation's IT policies when sharing information internally and externally (e.g. classifying emails/documents, encrypting sensitive information, sharing appropriate information on social media)
2. Securely access, synchronise and share information at work across different devices (e.g. manage email, calendar or appointment system via different devices)

**Communication** (three work tasks)

3. Communicate in the workplace digitally using messaging applications (e.g. email, Microsoft Teams, Zoom, Slack, internal intranet, WhatsApp)
4. Use workplace digital tools to create, share and collaborate with colleagues (e.g. Microsoft Teams, OneDrive, G-Suite, Office 365, WeTransfer, DropBox, WebEx, Slack)
5. Set up and manage an account on a professional online network/community/job site (e.g. LinkedIn, Total Jobs, Indeed)

**Transacting** (two work tasks)

6. Complete digital records on behalf of, or within my organisation (e.g. absence management, holidays, timesheets, expenses, tax returns)
7. Access salary and tax information digitally (e.g. password protected payslips, P60, P45)

**Problem solving** (four work tasks)

8. Find information online that helps me solve work related problems (e.g. search engines, IT helpdesk, software providers, peer networks)
9. Improve my skills and ability to do new things at work using online tutorials, learning platforms and how-to guides (e.g. LinkedIn Learning, YouTube, iDEA, Skillsoft, internal learning platforms)
10. Use appropriate software that is required of my day-to-day job (e.g. spreadsheets, online booking systems, HR management, workflow or sales management)
11. Improve my own and/or the organisation's productivity using digital tools (e.g. Trello, Microsoft Projects and Planner, Slack)

**Being safe and legal online** (nine work tasks)

12. Act with caution online and understand that there are risks and threats involved in carrying out activities online (e.g. use anti-virus software, classify and share information securely or avoid certain types of websites such as piracy websites)
13. Follow data protection guidelines online (e.g. following data storage and retention guidelines, not sharing or using other people's data or media such as movies or music without their consent)
14. Recognise suspicious links and know that clicking on these links or downloading unfamiliar attachments is a risk (e.g. spam/phishing emails, texts, pop ups)
15. Be careful with what I share online as I know that online activity produces a permanent record that can be accessed by others (e.g. publicly shared photos, forums, personal information or opinions)
16. Respond to requests for authentication for online accounts (e.g. resetting my password when I've forgotten it, two factor authentication, using a remote access key or authenticator app)
17. Identify secure websites (e.g. by looking for the padlock and https in the address bar)
18. Identify secure Wi-Fi networks to connect to (e.g. Wi-Fi networks where a unique password is required, trusted source or padlock next to Wi-Fi network)
19. Update my device software/operating systems when necessary to prevent viruses and other risks (e.g. enabling automatic updates, or installing when prompted to do so)
20. Set privacy and marketing settings for websites and my accounts (e.g. managing social media privacy settings, managing cookie settings, updating contact preferences)

For more information, visit the FutureDotNow website: [futuredotnow.uk/about-us/the-essential-digital-skills-framework](futuredotnow.uk/about-us/the-essential-digital-skills-framework)

# Appendix 3
# Technical Notes

## Overview of the methodology

This report aims to quantify the impact of digital skills on individual annual earnings and likelihood of employment, as well as to provide illustrative estimates on the wider economic impact of widespread digital upskilling. Our core analysis rests on two econometric models developed to robustly test these impacts. Below, we outline our framework, data sources, and approach, as well as the model specifications and regression statistics in the sections to come.

### Framework and construction of our Digital Skills Score

The framework we used to define and measure digital skills is the Essential Digital Skills framework championed by FutureDotNow and developed by the Department for Education.

This framework sets out the skills people need in order to safely benefit from, participate in, and contribute to the digital world[31] and, specifically within it, we focus on the essential skills relevant to the workplace. These are named the Work Essential Digital Skills. In our research, therefore, we define a person's level of digital skills by how many of the Work Essential Digital Skills tasks they are able to carry out independently.

In order to allow for greater variation in the data and for ease of interpretation, we constructed an index which assigns a 'Digital Skills Score' out of 100 to each respondent, based on how many Work Essential Digital Skills tasks they can carry out. The Work Essential Digital Skills framework, further, categorises the 20 essential work skills into 5 comprehensive pillars. These are:

- Communicating
- Problem Solving
- Handling Information and Content
- Transacting
- Being Safe and Legal Online.

The number of tasks included within each pillar is not symmetrical. For instance, while 'Being Safe and Legal Online' includes nine tasks, 'Transacting' has only two. In our index, therefore, we weight each pillar equally to ensure a balanced score, rewarding respondents who are well-rounded across all pillars.

### Data

Our econometric analysis is based on cross-sectional data collected through a consumer survey of 2000 individuals, ran by our survey partner Opinium in late December of 2024. The survey captured key demographic characteristics, salary, working status, digital skills, and access to devices and Internet connection.

31 FutureDotNow, 2025: https://futuredotnow.uk/about-us/the-essential-digital-skills-framework/

The survey data was weighted to ensure our sample was nationally representative. However, as the survey was conducted online, there was a risk of bias – potentially underrepresenting individuals with the lowest level of digital skills, who may be unable or unwilling to participate in an online survey. To address this, we applied an additional weighting correction using data from Lloyds' 2024 Consumer Digital Index[32] on the distribution of digital skills across the labour force, which is based on a telephone survey instead.

Given our reliance on Lloyds' data for weighting, we therefore designed our survey to align closely with their methodology. In particular, we framed questions on Work Essential Digital Skills to match Lloyd's approach as closely as possible. An example of our survey question format is provided below:

**For each of the following statements, please select whether this is something you could work out how to do independently without help.**

1. Communicate in the workplace digitally using messaging applications (e.g. Email, Microsoft Teams, Zoom, Slack, internal intranet, WhatsApp)

**Response Options**

1. This is something I do, or have done in the past.
2. I haven't done this, but I would be confident that I could do it if asked.
3. I haven't done this, and I would not be confident that I could do it if asked.

We coded respondents' answers to questions on digital skills in a binary way; those who chose options 1 or 2 were defined as being able to do the task, and those who chose option 3 were defined as not being able to do it.

For the calculation of wider economy impacts, we used national statistics on earnings from the Annual Survey of Hours and Earnings (ASHE) and on the size of the labour force from the Labour Force Survey (LFS) for 2024, both published by the Office for National Statistics (ONS).

### Econometric models

We developed two econometric models: a linear regression model for estimating the impact of digital skills on earnings and a logistic regression for estimating the impact of digital skills on likelihood of employment. For the development of the models, we restricted our sample to respondents in the labour force, whether in employment or seeking employment, which left us with a working weighted sample of 1,251.

Chosen and alternative specifications, as well as regression statistics for both models, are included in below.

For the subgroup results included in Section 2, we multiplied the specific coefficient obtained from each subset regression by the average gap in Digital Skill Score between lower and higher scorers within each subgroup. This gave us the percentage changes in salary associated with lower scorers learning new skills, which we applied to lower quartile average wages for the different subgroups, obtained from ASHE.

32 2024 Consumer Digital Index, Lloyds, 2024: https://www.lloydsbank.com/assets/media/pdfs/banking_with_us/whats-happening/lb-consumer-digital-index-2024-report.pdf

**Estimating wider economy impacts**

Here, we calculated the wider economic impact of one main hypothetical scenario. This is the scenario in which everyone learns to do all 20 Work Essential Digital Skills tasks. Our approach focuses on the direct impact of digital upskilling on wages and employment and does not consider whether the economy has the capacity to deliver training at scale, nor broader general equilibrium effects such as changes in employer demand, substitution effects, or long-term structural shifts in the labour market.

For the calculation of total earnings uplift, we estimated first the average percentage change in salary associated with lower scorers moving to the median. We then multiplied this estimate by the ASHE-derived 25$^{th}$ quartile wage in 2024, and subsequently by the number of workers concerned in the economy in 2024. We did this separately for full and part-time workers, and repeated this process for estimating total earnings in the second hypothetical scenario in which all workers were able to do the 20 Work Essential Digital Skills tasks.

In order to estimate how an uplift to total earnings would impact GVA, we first estimated the resulting total Compensation of Employees (COE) – which includes all employee benefits in addition to wages. We then estimated the associated uplift in Gross Value Added (GVA) using the COE-GVA ratio from ONS' 2024 Blue Book estimates. Our measure of business profitability, i.e. Gross Operating Surplus (GOS) was derived using a similar approach. The assumptions underlying these economic ratios are explicitly detailed in Section 2.

For the estimation of employment, we looked specifically at our sample of unemployed people, and applied the distribution of digital skills within that group to the total estimate of unemployed people in the economy, obtained from the LFS. We then calculated the increase in probability of employment from digital upskilling at different initial skill levels, in order to estimate the total number of jobs added from increased digital skills.

We calculated the resulting impact of this employment uplift to earnings, GVA, and GOS, in the same way as outlined above.

## Description of variables

Before running our econometric models, our survey data had to be cleaned, and new variables created. Below is a description of some of the variables used:

- We coded **education** as a categorical variable broken down into eight categories, these were:
  - Level 1: Entry Level (no formal qualifications)
  - Level 2: GCSE, Standard Grades or equivalent, such as BTEC, S/NVQ
  - Level 3: A levels, international Baccalaureate diploma, or an advanced apprenticeship
  - Level 4: a certificate of higher education or higher apprenticeship
  - Level 5: a foundation degree
  - Level 6: a BA or BSc degree
  - Level 7: a postgraduate qualification such as MA, MSc, or PGCE
  - Level 8: a PhD
- **Organisation size** was also coded into a categorical variable with four categories:
  - Micro firm: 0 to 9 employees
  - Small firm: 10 to 49 employees

  - Mid-sized firm: 50 to 249 employees
  - Large firm: 250+ employees
- Certain **industries** were aggregated so as to avoid small sample sizes, resulting in another categorical variable with six categories:
  - High-skilled services: Information and Communication; Financial and Insurance services; and Professional, Scientific, and Technical Activities
  - Industrial: Construction; Manufacturing; and Mining, quarrying, and utilities
  - Trade: Retail and Manufacturing
  - Agriculture: Agriculture, Forestry, and Fishing
  - Public services: Health; Public Administration and Defence; Education; Arts, Entertainment, Recreation and Other Services
  - Other sectors: Accommodation and Food Services; Transport and Storage; Business Administration and Support Services; Automative/Motor Trades; Property; Other Sectors
- **Region** was coded as a categorical variable, with nine categories for the English regions and one for each of Wales, Northern Ireland, and Scotland. Regional sample sizes were for the most part sufficiently large to run our analysis. In Wales and Northern Ireland they were slightly low, at around 40 each, which should be taken into consideration.

Our main independent variable **'Index Score'** assigns a digital skills score between 0 and 100 to each respondent according to the number of digital tasks they can do, and is therefore a continuous variable. We also evaluated using a categorical variable instead, based on the number of tasks someone could perform. We tested our earnings model, described in more detail below, with both a categorical 'Number of skills' variable and our continuous index. Ultimately, using a continuous 'Index Score' variable proved to deliver both statistically significant results and positive regression statistics, which was not the case for the categorical variable.

While using a categorical variable for number of tasks would have been intuitive, the above explanation coupled with the need to weight Work Essential Digital Skills pillars equally highlights the benefits of using an index. Our index allowed us to apply weights to each pillar of questions. This weighting was an important part of our methodology, as it determined who we were defining to be 'digitally skilled' in our sample. In essence, not weighting pillars equally would have rewarded number of tasks, even if concentrated only in one pillar with lots of tasks within it such as 'Being Safe and Legal Online'. Instead, weighting pillars equally allowed us to define those individuals who were most 'well-rounded' across all pillars as those most digitally skilled.

A limitation of using a continuous index is losing some ease of interpretation. Weighting all pillars equally means assigning some tasks (those in pillars with a particularly low number of tasks) a greater weight than others. This may result in two individuals with the same index score being able to do a different number of tasks. Given the scope of our analysis here, however, this does not pose a problem. Every task covered by the Work Essential Digital Skills framework is deemed essential for the workplace. Therefore, the main interpretation of our index we are concerned with was that of people learning to all 20 tasks (i.e. reaching a score of 100). A score of 100 is interpreted in the same way for every respondent, hence fulfilling our purposes.

## Earnings linear regression model

Our earnings multiple linear regression model aims to test the relationship between our dependent variable (salaries) and our independent variable (digital skills) while controlling for other variables which are relevant to a person's earnings. It is applied to our sample of people in the labour force, previously weighted so as to ensure national representativeness and lack of bias as described above.

The model is specified as follows:

$$\begin{aligned}\ln(income)_i = \ & \alpha + \beta_1 Index\ score_i + \beta_2 Full\text{-}time_i + \beta_3 Manager_i + \beta_4 Years\ of\ experience_i \\ & + \beta_5 Male_i + \beta_{6j} Organisation\ Size_i + \beta_{7k} Industry_i + \beta_{8l} Region_i \\ & + \beta_{9m} Education_i\end{aligned}$$

Where,

- $\ln(income)_{ijkl}$ is the natural logarithmic value of income of respondent *i*[33]
- *α* is the constant.
- $\beta_n$ is the coefficient of a certain variable on the level of income.
- $Index\ score_i$ is the level of digital literacy of respondent *i* from 0 to 100.
- $Male_i$ , $Full\text{-}time_i$ and $Manager_i$ are dummy variables which equal to 1 when respondent *i* is male, working full-time, and has a managerial role, respectively, otherwise they are 0.
- $Years\ of\ experience_i$ is a continuous variable measuring the number of years of labour market experience of respondent *i*.
- $Organisation\ size_i$ is the size of the company where respondent *i* is employed, which can be one of *j* categories. When using a categorical variable, one of the categories ought to be dropped so as to avoid multiple collinearity. In this case the variable dropped is 'Large firms'. Therefore, the estimates on the other three organisation size variables are interpreted in reference to large firms.
- $Industry_i$ is the industry respondent *i* works in, which can be one of *k* categories. The variable dropped in this case is Agriculture.
- $Region_i$ is the region respondent *i* lives in, which can be one of *l* categories. The variable dropped in this case is the East Midlands.
- $Education_i$ is the level of education obtained by respondent *i*, which can be one of *m* categories. The variable dropped in this case is Education: Level 1.

Results for the most general iteration of our model, that is, before our dataset is further broken down into smaller subsets for subset analysis, is presented in Table 2.

33 Our model, therefore, is a log-linear model. Taking the natural logarithm of income is helpful for multiple reason. It helps normalise our salary data which tends to be right-skewed as most people earn lower salaries and only a few earn higher salaries, It also helps stabilise the variance of residuals and hence reduce heteroskedasticity.

Table 2: Results of multiple linear regression on income among people in the labour force

| Number of observations: 1,019 | | | | | | |
|---|---|---|---|---|---|---|
| Adjusted R-squared: 0.4349 | | | | | | |
| Variable | Coefficient | Standard Error[34] | t-value | p-value | [95% Confidence Interval] | |
| Constant | 9.5863 | 0.2111 | 45.4037 | 0.0000***[35] | 9.1720 | 10.0006 |
| Index Score | 0.0022 | 0.0010 | 2.1295 | 0.0335** | 0.0002 | 0.0042 |
| Full-time | 0.4591 | 0.0543 | 8.4536 | 0.0000*** | 0.3525 | 0.5657 |
| Manager | 0.3231 | 0.0416 | 7.7692 | 0.0000*** | 0.2415 | 0.4047 |
| Years of experience | 0.0084 | 0.0035 | 2.3651 | 0.0182** | 0.0014 | 0.0153 |
| Male | 0.0744 | 0.0407 | 1.8276 | 0.0679* | -0.0055 | 0.1542 |
| Organisation size: Mid-sized firms | -0.0899 | 0.0437 | -2.0562 | 0.0400** | -0.1758 | -0.0041 |
| Organisation size: Micro firms | -0.4354 | 0.0690 | -6.3129 | 0.0000*** | -0.5708 | -0.3001 |
| Organisation size: Small firms | -0.1566 | 0.0563 | -2.7833 | 0.0055*** | -0.2670 | -0.0462 |
| Industry: High-skilled services | 0.1673 | 0.1502 | 1.1142 | 0.2655 | -0.1273 | 0.4620 |
| Industry: Industrial | 0.0787 | 0.1494 | 0.5267 | 0.5985 | -0.2145 | 0.3718 |
| Industry: Other sectors | -0.1177 | 0.1505 | -0.7821 | 0.4343 | -0.4130 | 0.1776 |
| Industry: Public services | -0.0684 | 0.1498 | -0.4564 | 0.6482 | -0.3623 | 0.2256 |
| Industry: Trade | -0.3471 | 0.1575 | -2.2044 | 0.0277** | -0.6561 | -0.0381 |
| Region: East of England | 0.0530 | 0.0830 | 0.6387 | 0.5232 | -0.1099 | 0.2159 |
| Region: London | 0.3387 | 0.0841 | 4.0263 | 0.0001*** | 0.1736 | 0.5038 |
| Region: North East | 0.2979 | 0.1016 | 2.9326 | 0.0034*** | 0.0986 | 0.4972 |
| Region: North West | 0.1487 | 0.0980 | 1.5174 | 0.1295 | -0.0436 | 0.3409 |
| Region: Northern Ireland | -0.0607 | 0.1326 | -0.4578 | 0.6472 | -0.3209 | 0.1995 |
| Region: Scotland | 0.1918 | 0.0866 | 2.2146 | 0.0270** | 0.0219 | 0.3618 |
| Region: South East | 0.0391 | 0.0938 | 0.4168 | 0.6769 | -0.1450 | 0.2232 |
| Region: South West | 0.0652 | 0.0969 | 0.6734 | 0.5008 | -0.1249 | 0.2554 |
| Region: Wales | 0.0328 | 0.1137 | 0.2888 | 0.7728 | -0.1902 | 0.2559 |

34 Standard errors have for all regressions presented here been calculated to be heteroskedasticity and cluster robust.

35 * denotes that the coefficient is significant at the 10% level (i.e. the p-value is below 0.10), ** denotes that it is significant at the 5% level (i.e. the p-value is below 0.05), and *** denotes that it is significant at the 1% level (i.e. the p-value is below 0.01)

| | | | | | | |
|---|---|---|---|---|---|---|
| Region: West Midlands | 0.0433 | 0.0953 | 0.4550 | 0.6492 | -0.1436 | 0.2303 |
| Region: Yorkshire and the Humberside | 0.1206 | 0.0971 | 1.2423 | 0.2144 | -0.0699 | 0.3110 |
| Education: Level 2 | -0.1560 | 0.1150 | -1.3557 | 0.1755 | -0.3817 | 0.0698 |
| Education: Level 3 | -0.1241 | 0.1164 | -1.0654 | 0.2869 | -0.3525 | 0.1044 |
| Education: Level 4 | -0.1738 | 0.1229 | -1.4138 | 0.1577 | -0.4150 | 0.0674 |
| Education: Level 5 | -0.1652 | 0.1349 | -1.2253 | 0.2207 | -0.4299 | 0.0994 |
| Education: Level 6 | -0.0445 | 0.1131 | -0.3937 | 0.6939 | -0.2664 | 0.1774 |
| Education: Level 7 | 0.0452 | 0.1154 | 0.3920 | 0.6951 | -0.1812 | 0.2716 |
| Education: Level 8 | 0.1851 | 0.1482 | 1.2491 | 0.2119 | -0.1057 | 0.4759 |

*Source: Opinium, Cebr analysis*

Our adjusted R-squared is of 0.4349, meaning that approximately 43.5% of variation in salaries is captured by our model.

The main estimate of interest from this regression is that on index score, which is of **0.0022**, and is interpreted as follows: **an increase of 1 basis point in the index score increases income by 0.22%.** In this case, the index score has a p-value of 0.0335, which means that there is only 3.4% chance that the index score does not affect the income. Therefore, the result is statistically significant at a 5% confidence level, which is the standard for this type of analysis. Thus, we can conclude that digital skill level has a positive effect on income.

Below are presented the regressions run on specific subsets of our labour market survey sample. Although we tested the impact of index score on earnings for every region, industry, and organisation size, we here only present the regressions in which the coefficient of 'Index Score' was statistically significant and the adjusted R-squared above 40%. In certain cases, such as in the South West, models were kept more efficient so as to avoid collinearity.

**Region – London:**

Table 3: Results of multiple linear regression on income among people in London

| Number of observations: 110 | | | | | | |
|---|---|---|---|---|---|---|
| Adjusted R-squared: 0.5148 | | | | | | |
| Variable | Coefficient | Standard Error | t-value | p-value | [95% Confidence Interval] | |
| Constant | 9.7670 | 0.3779 | 25.8434 | 0.0000*** | 9.0180 | 10.5160 |
| Index Score | 0.0050 | 0.0024 | 2.0803 | 0.0398** | 0.0002 | 0.0097 |
| Full-time | 0.2581 | 0.1134 | 2.2749 | 0.0249** | 0.0332 | 0.4829 |
| Manager | 0.5311 | 0.0958 | 5.5429 | 0.0000*** | 0.3412 | 0.7210 |
| Years of experience | 0.0195 | 0.0066 | 2.9655 | 0.0037*** | 0.0065 | 0.0326 |
| Male | 0.0163 | 0.0864 | 0.1892 | 0.8503 | -0.1549 | 0.1876 |
| Organisation size: Mid-sized firms | -0.2752 | 0.0955 | -2.8800 | 0.0048*** | -0.4645 | -0.0858 |
| Organisation size: Micro firms | -0.5061 | 0.1503 | -3.3660 | 0.0011*** | -0.8040 | -0.2081 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Organisation size: Small firms | -0.2285 | 0.1478 | -1.5458 | 0.1250 | -0.5215 | 0.0645 |
| Industry: High-skilled services | -0.2039 | 0.1322 | -1.5422 | 0.1259 | -0.4659 | 0.0581 |
| Industry: Industry | -0.1916 | 0.1244 | -1.5395 | 0.1266 | -0.4381 | 0.0550 |
| Industry: Other sectors | -0.2643 | 0.1336 | -1.9786 | 0.0504* | -0.5290 | 0.0004 |
| Industry: Public services | -0.5839 | 0.1720 | -3.3949 | 0.0010*** | -0.9247 | -0.2430 |
| Industry: Trade | -0.0809 | 0.2043 | -0.3959 | 0.6929 | -0.4858 | 0.3240 |
| Education: Level 2 | -0.2000 | 0.1959 | -1.0210 | 0.3095 | -0.5883 | 0.1882 |
| Education: Level 3 | 0.1045 | 0.2162 | 0.4833 | 0.6299 | -0.3240 | 0.5330 |
| Education: Level 4 | -0.0968 | 0.2312 | -0.4186 | 0.6763 | -0.5550 | 0.3614 |
| Education: Level 5 | 0.0296 | 0.1876 | 0.1576 | 0.8751 | -0.3422 | 0.4013 |
| Education: Level 6 | 0.0882 | 0.1827 | 0.4829 | 0.6301 | -0.2738 | 0.4502 |
| Education: Level 7 | 0.0387 | 0.3304 | 0.1170 | 0.9071 | -0.6161 | 0.6934 |
| Education: Level 8 | 9.7670 | 0.3779 | 25.8434 | 0.0000*** | 9.0180 | 10.5160 |

*Source: Opinium, Cebr analysis*

**Region - South West:**

Table 4:Results of multiple linear regression on income among people in the South West of England

| Number of observations: 74 | | | | | | |
|---|---|---|---|---|---|---|
| Adjusted R-squared: 0.4944 | | | | | | |
| Variable | Coefficient | Standard Error | t-value | p-value | [95% Confidence Interval] | |
| Constant | 9.3153 | 0.5157 | 18.0621 | 0.0000*** | 8.2877 | 10.3430 |
| Index Score | 0.0065 | 0.0034 | 1.9384 | 0.0564* | -0.0002 | 0.0132 |
| Full-time | 0.5047 | 0.1346 | 3.7506 | 0.0003*** | 0.2366 | 0.7729 |
| Manager | 0.3490 | 0.1039 | 3.3595 | 0.0012*** | 0.1420 | 0.5559 |
| Years of experience | -0.0018 | 0.0156 | -0.1180 | 0.9064 | -0.0330 | 0.0293 |
| Male | 0.0713 | 0.1186 | 0.6012 | 0.5495 | -0.1650 | 0.3076 |
| Organisation size: Mid-sized firms | -0.2653 | 0.1682 | -1.5768 | 0.1191 | -0.6005 | 0.0700 |
| Organisation size: Micro firms | -0.5126 | 0.1611 | -3.1820 | 0.0021*** | -0.8336 | -0.1916 |
| Organisation size: Small firms | -0.1000 | 0.1350 | -0.7408 | 0.4612 | -0.3690 | 0.1690 |
| Industry: High-skilled services | 0.2667 | 0.3581 | 0.7446 | 0.4589 | -0.4469 | 0.9802 |
| Industry: Industry | 0.1879 | 0.3200 | 0.5871 | 0.5589 | -0.4498 | 0.8256 |
| Industry: Other sectors | -0.0286 | 0.3273 | -0.0874 | 0.9306 | -0.6807 | 0.6235 |
| Industry: Public services | 0.0693 | 0.3198 | 0.2166 | 0.8291 | -0.5679 | 0.7065 |
| Industry: Trade | -0.5435 | 0.3567 | -1.5236 | 0.1319 | -1.2543 | 0.1673 |

*Source: Opinium, Cebr analysis*

**Region - North West:**

Table 5: Results of multiple linear regression on income among people in the North West of England

| Number of observations: 100 | | | | | | |
|---|---|---|---|---|---|---|
| Adjusted R-squared: 0.4398 | | | | | | |
| Variable | Coefficient | Standard Error | t-value | p-value | [95% Confidence Interval] | |
| Constant | 9.6137 | 0.4907 | 19.5908 | 0.0000*** | 8.6401 | 10.5873 |
| Index Score | 0.0078 | 0.0022 | 3.4833 | 0.0007*** | 0.0034 | 0.0122 |
| Full-time | 0.1407 | 0.1905 | 0.7385 | 0.4620 | -0.2372 | 0.5185 |
| Manager | 0.0238 | 0.1307 | 0.1818 | 0.8561 | -0.2356 | 0.2831 |
| Years of experience | 0.0039 | 0.0140 | 0.2806 | 0.7796 | -0.0239 | 0.0317 |
| Male | 0.0076 | 0.1374 | 0.0552 | 0.9561 | -0.2650 | 0.2802 |
| Organisation size: Mid-sized firms | -0.1277 | 0.1053 | -1.2136 | 0.2278 | -0.3366 | 0.0811 |
| Organisation size: Micro firms | -0.7672 | 0.2216 | -3.4622 | 0.0008*** | -1.2069 | -0.3276 |
| Organisation size: Small firms | -0.4988 | 0.2638 | -1.8907 | 0.0616* | -1.0221 | 0.0246 |
| Industry: Industry | 0.0418 | 0.1591 | 0.2625 | 0.7935 | -0.2739 | 0.3575 |
| Industry: Other sectors | -0.3025 | 0.1820 | -1.6617 | 0.0997 | -0.6636 | 0.0587 |
| Industry: Public services | -0.6164 | 0.1869 | -3.2980 | 0.0013*** | -0.9872 | -0.2456 |
| Industry: Trade | -0.0347 | 0.2571 | -0.1348 | 0.8930 | -0.5447 | 0.4753 |
| Education: Level 2 | 0.3470 | 0.2327 | 1.4916 | 0.1390 | -0.1146 | 0.8086 |
| Education: Level 3 | 0.2712 | 0.2238 | 1.2118 | 0.2284 | -0.1728 | 0.7153 |
| Education: Level 4 | 0.1193 | 0.2285 | 0.5220 | 0.6028 | -0.3340 | 0.5726 |
| Education: Level 5 | 0.4563 | 0.3346 | 1.3638 | 0.1757 | -0.2075 | 1.1201 |
| Education: Level 6 | 0.5338 | 0.2591 | 2.0602 | 0.0420** | 0.0198 | 1.0478 |
| Education: Level 7 | 0.5771 | 0.2384 | 2.4208 | 0.0173** | 0.1041 | 1.0500 |
| Education: Level 8 | 0.4944 | 0.4808 | 1.0282 | 0.3063 | -0.4596 | 1.4483 |

*Source: Opinium, Cebr analysis*

**Industry – High-skilled services:**

While for our regional subset analysis our models were practically identical to our general model, for the industrial analysis as for that of different organisation sizes, the inclusion of interaction terms considerably improved the fit of the models. Therefore, instead of creating new samples with subsets of the data, in these cases we used interaction terms and set the variable of interest as the reference category to be dropped (so as to avoid multiple collinearity). The coefficient on Index score, therefore, is interpreted as the effect of index score on salaries for individuals who are part of, in these cases, the high-skilled services industry or a mid-sized firm.

Table 6: Results of multiple linear regression on income among people in the high-skilled services industry

| Number of observations: 1,010 | | | | | | |
|---|---|---|---|---|---|---|
| Adjusted R-squared: 0.4477 | | | | | | |
| Variable | Coefficient | Standard Error | t-value | p-value | [95% Confidence Interval] | |
| Constant | 9.4488 | 0.2421 | 39.0317 | 0.0000 | 8.9738 | 9.9238 |
| Index score | 0.0055 | 0.0020 | 2.7139 | 0.0068*** | 0.0015 | 0.0094 |
| Industry: Industry | 0.5240 | 0.2566 | 2.0418 | 0.0414** | 0.0204 | 1.0275 |
| Industry: Other Sector | -0.2567 | 0.2426 | -1.0580 | 0.2903 | -0.7328 | 0.2194 |
| Industry: Public services | 0.3008 | 0.2146 | 1.4019 | 0.1613 | -0.1203 | 0.7220 |
| Industry: Trade | -0.1323 | 0.4154 | -0.3184 | 0.7503 | -0.9474 | 0.6829 |
| Male | 0.0723 | 0.0396 | 1.8235 | 0.0685* | -0.0055 | 0.1501 |
| Full-time | 0.4617 | 0.0534 | 8.6450 | 0.0000*** | 0.3569 | 0.5665 |
| Education: Level 2 | -0.1751 | 0.1080 | -1.6210 | 0.1053 | -0.3870 | 0.0369 |
| Education: Level 3 | -0.1531 | 0.1098 | -1.3951 | 0.1633 | -0.3685 | 0.0623 |
| Education: Level 4 | -0.2010 | 0.1178 | -1.7070 | 0.0881* | -0.4322 | 0.0301 |
| Education: Level 5 | -0.1895 | 0.1303 | -1.4550 | 0.1460 | -0.4452 | 0.0661 |
| Education: Level 6 | -0.0647 | 0.1069 | -0.6051 | 0.5452 | -0.2744 | 0.1450 |
| Education: Level 7 | 0.0304 | 0.1085 | 0.2804 | 0.7792 | -0.1824 | 0.2432 |
| Education: Level 8 | 0.1744 | 0.1445 | 1.2066 | 0.2279 | -0.1092 | 0.4579 |
| Manager | 0.3271 | 0.0408 | 8.0160 | 0.0000*** | 0.2470 | 0.4071 |
| Years of experience | 0.0089 | 0.0036 | 2.4690 | 0.0137** | 0.0018 | 0.0160 |
| Region: East of England | 0.0670 | 0.0828 | 0.8093 | 0.4185 | -0.0955 | 0.2295 |
| Region: London | 0.3386 | 0.0833 | 4.0644 | 0.0001*** | 0.1751 | 0.5020 |
| Region: North East | 0.2873 | 0.1027 | 2.7978 | 0.0052*** | 0.0858 | 0.4888 |
| Region: North West | 0.1671 | 0.0961 | 1.7401 | 0.0821* | -0.0213 | 0.3556 |
| Region: Northern Ireland | -0.0601 | 0.1252 | -0.4799 | 0.6314 | -0.3057 | 0.1856 |
| Region: Scotland | 0.2000 | 0.0885 | 2.2589 | 0.0241** | 0.0263 | 0.3737 |
| Region: South East | 0.0194 | 0.0929 | 0.2090 | 0.8345 | -0.1628 | 0.2016 |
| Region: South West | 0.0679 | 0.1030 | 0.6598 | 0.5095 | -0.1341 | 0.2700 |
| Region: Wales | 0.0401 | 0.1137 | 0.3528 | 0.7243 | -0.1829 | 0.2631 |
| Region: West Midlands | 0.0604 | 0.0922 | 0.6554 | 0.5124 | -0.1205 | 0.2413 |
| Region: Yorkshire and the Humber | 0.1161 | 0.0977 | 1.1882 | 0.2350 | -0.0756 | 0.3078 |
| Organisation size: Mid-sized firms | -0.0855 | 0.0435 | -1.9681 | 0.0493** | -0.1708 | -0.0003 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Organisation size: Micro firms | -0.4396 | 0.0694 | -6.3348 | 0.0000*** | -0.5758 | -0.3034 |
| Organisation size: Small firms | -0.1673 | 0.0542 | -3.0861 | 0.0021*** | -0.2736 | -0.0609 |
| Interaction: Index score*Industry-Industry | -0.0069 | 0.0027 | -2.5598 | 0.0106** | -0.0122 | -0.0016 |
| Interaction: Index score*Industry-Other sectors | 0.0004 | 0.0026 | 0.1435 | 0.8860 | -0.0048 | 0.0056 |
| Interaction: Index score*Industry-Public services | -0.0060 | 0.0023 | -2.6174 | 0.0090*** | -0.0104 | -0.0015 |
| Interaction: Index score*Industry-Trade | -0.0041 | 0.0046 | -0.9038 | 0.3663 | -0.0131 | 0.0048 |

*Source: Opinium, Cebr analysis*

### Organisation Size – Mid-sized firms:

Table 7: Results of multiple linear regression on income among people employed in mid-sized firms

| Number of observations: 1,016 | | | | | | |
|---|---|---|---|---|---|---|
| Adjusted R-squared: 0.4374 | | | | | | |
| Variable | Coefficient | Standard Error | t-value | p-value | [95% Confidence Interval] | |
| Constant | 9.4514 | 0.2350 | 40.2119 | 0.0000*** | 8.9900 | 9.9126 |
| Index score | 0.0026 | 0.0014 | 1.8979 | 0.0580* | -0.0001 | 0.0053 |
| Organisation size: Large firms | 0.1006 | 0.1540 | 0.6537 | 0.5134 | -0.2015 | 0.4027 |
| Organisation size: Micro firms | -0.4205 | 0.2712 | -1.5505 | 0.1213 | -0.9528 | 0.1117 |
| Organisation size: Small firms | 0.2808 | 0.2251 | 1.2474 | 0.2125 | -0.1609 | 0.7225 |
| Male | 0.0715 | 0.0408 | 1.7518 | 0.0801* | -0.0086 | 0.1515 |
| Full-time | 0.4641 | 0.0540 | 8.5940 | 0.0000*** | 0.3581 | 0.5701 |
| Manager | 0.3234 | 0.0408 | 7.9343 | 0.0000*** | 0.2435 | 0.4034 |
| Years of experience | 0.0081 | 0.0035 | 2.2808 | 0.0228** | 0.0011 | 0.0151 |
| Education: Level 2 | -0.1652 | 0.1136 | -1.4539 | 0.1463 | -0.3881 | 0.0578 |
| Education: Level 3 | -0.1299 | 0.1160 | -1.1200 | 0.2630 | -0.3574 | 0.0977 |
| Education: Level 4 | -0.1816 | 0.1215 | -1.4944 | 0.1354 | -0.4200 | 0.0569 |
| Education: Level 5 | -0.1658 | 0.1340 | -1.2375 | 0.2162 | -0.4288 | 0.0971 |
| Education: Level 6 | -0.0500 | 0.1108 | -0.4513 | 0.6519 | -0.2675 | 0.1675 |
| Education: Level 7 | 0.0366 | 0.1133 | 0.3233 | 0.7465 | -0.1858 | 0.2590 |
| Education: Level 8 | 0.1815 | 0.1475 | 1.2303 | 0.2189 | -0.1080 | 0.4710 |
| Region: East of England | 0.0596 | 0.0846 | 0.7048 | 0.4811 | -0.1063 | 0.2255 |
| Region: London | 0.3419 | 0.0860 | 3.9735 | 0.0001*** | 0.1730 | 0.5107 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Region: North East | 0.3027 | 0.1020 | 2.9662 | 0.0031*** | 0.1024 | 0.5029 |
| Region: North West | 0.1566 | 0.0986 | 1.5882 | 0.1125 | -0.0369 | 0.3501 |
| Region: Northern Ireland | -0.0532 | 0.1323 | -0.4020 | 0.6878 | -0.3128 | 0.2064 |
| Region: Scotland | 0.1942 | 0.0890 | 2.1812 | 0.0294** | 0.0195 | 0.3689 |
| Region: South East | 0.0256 | 0.0956 | 0.2678 | 0.7889 | -0.1619 | 0.2131 |
| Region: South West | 0.0732 | 0.0968 | 0.7562 | 0.4497 | -0.1168 | 0.2632 |
| Region: Wales | 0.0407 | 0.1154 | 0.3521 | 0.7248 | -0.1859 | 0.2672 |
| Region: West Midlands | 0.0465 | 0.0975 | 0.4765 | 0.6338 | -0.1449 | 0.2378 |
| Region: Yorkshire and the Humber | 0.1297 | 0.0987 | 1.3143 | 0.1890 | -0.0639 | 0.3233 |
| Industry: High-skilled services | 0.1824 | 0.1498 | 1.2178 | 0.2236 | -0.1115 | 0.4763 |
| Industry: Industry | 0.0852 | 0.1495 | 0.5697 | 0.5690 | -0.2082 | 0.3786 |
| Industry: Other Sector | -0.1011 | 0.1499 | -0.6745 | 0.5001 | -0.3952 | 0.1930 |
| Industry: Public services | -0.0514 | 0.1497 | -0.3436 | 0.7312 | -0.3452 | 0.2423 |
| Industry: Trade | -0.3187 | 0.1547 | -2.0608 | 0.0396** | -0.6222 | -0.0152 |
| Interaction: Index score*Organisation size-Large firms | -0.0002 | 0.0017 | -0.0936 | 0.9254 | -0.0035 | 0.0032 |
| Interaction: Index score*Organisation size-Micro firms | 0.0010 | 0.0031 | 0.3355 | 0.7373 | -0.0050 | 0.0071 |
| Interaction: Index score*Organisation size-Small firms | -0.0042 | 0.0025 | -1.6822 | 0.0928* | -0.0091 | 0.0007 |

*Source: Opinium, Cebr analysis*

**Alternative specifications tested and limitations**

- Endogeneity and the use of instrumental variables: Given the nature of our analysis, endogeneity was a possible concern. In particular, there could have been reverse causality between our dependent and our independent variables. It's possible that higher earners have more digital skills because their industries particularly incentivise digital skills training, or because they have more disposable income to invest on their personal upskilling.
  In order to explore this possibility, we tested a model with instrumental variables taken from our survey data. The two instruments used were whether a person had received digital skills training outside of the workplace, and whether they had learnt any new digital skills in the past 12 months. For the latter, additionally, we restricted responses to those who had not responded "Yes, frequently" so as to improve exogeneity. We tested overidentification and the strength of our instruments, with both tests passing successfully and hence confirming the validity of the instruments.
  We found, however, no evidence of endogeneity. Our Wu-Hausman test had a reported p-value of 0.184, above the three conventional thresholds, and therefore showed that there was no endogeneity between our dependent and independent variables.

- Omitted variable bias: while including numerous control variables and obtaining satisfactory adjusted R-squared statistics, there are two variables in particular that we were not able to proxy for and that might introduce some degree of bias. These are an individual's self-confidence and an individual's proficiency at more advanced digital skills.
  The first could be introduced through the self-reported nature of our survey. It could be the case that respondents who reported being able to do a large number of digital tasks were also more self-confident, and vice versa for those who reported a lower number of tasks. Self-confidence could then be related to an individual's salary and therefore be slightly confounding our estimates.
  The second could be introduced because of the Work Essential Digital Skills framework, and therefore our survey, capturing only an individual's foundational digital skills level. Individuals who can do all 20 tasks, for instance, may also be more likely to do more advanced digital tasks such as coding or using industry specific software. This higher ability could therefore also be biasing our coefficients.
  Overall, nevertheless, our positive R-squared statistics indicate that a satisfactory proportion of variation in salaries is captured by our models.

## Employment logistic regression model

In order to test the relationship between employment and digital skills, we used a logistic regression model that estimated the impact of digital skills on an individual's likelihood of employment.

The model is specified as follows:

$$\begin{aligned}\text{logit}(Employment)_i &\\ &= \alpha + \beta_1 Index\ score_i + \beta_2 Disability_i + \beta_3 Age\_squared_i \\ &+ \beta_4 Years\ of\ experience_i + \beta_5 London_i + \beta_{6m} Education_i\end{aligned}$$

Where,

- $\text{logit}(Employment)_i$ is the log-odds of employment for individual *i*
- $\alpha$ is the constant.
- $\beta_n$ is the coefficient of a certain variable on the log-odds of employment.
- $Index\ score_i$ is the level of digital literacy of respondent *i* from 0 to 100.
- $Disability_i\ and\ London_i$ are dummy variables which equal to 1 when respondent *I* has a disability, or works in London, respectively, otherwise they are 0.
- $Years\ of\ experience_i$ is a categorical variable measuring the number of years of labour market experience of respondant *i*.
- $Education_i$ is the level of education obtained by respondent *i*, which can be one of *m* categories.

Below are the results for our logistic regression of employment on digital skills. Due to the size of our sample of unemployed respondents we did not here run any subset analysis, since, while large enough to run our general model on, subdivisions of it would have been too small. In order to maximise model efficiency, additionally, we removed categorical controls which weren't significantly impacting the fit of the model.

Table 8: Results of logistic regression on employment among people in the labour force

| Number of observations: 1,287 | | | | | | |
|---|---|---|---|---|---|---|
| Wald Chi-squared: 79.81 McFadden Pseudo-R squared: 0.1527 | | | | | | |
| Variable | Coefficient | Standard Error | Z value | p-value | [95% Confidence Interval] | |
| Constant | 1.217 | 0.593 | 2.05 | 0.040** | 0.542 | 2.379 |
| Index Score | 0.009 | 0.004 | 2.05 | 0.040** | 0.0003 | 0.170 |
| Disability | - 0.844 | 0.292 | -2.89 | 0.004*** | -1.416 | -0.271 |
| Age squared | -0.003 | 0.001 | -2.13 | 0.033** | -0.001 | -0.000 |
| London | -0.455 | 0.377 | -1.20 | 0.228 | -1.194 | 0.285 |
| Experience: Moderate 4-8 years | 1.969 | 0.427 | 4.61 | 0.000*** | 1.133 | 2.806 |
| Experience: High 13-18 years | 2.190 | 0.437 | 5.01 | 0.000*** | 1.333 | 3.047 |
| Experience: Very high 20+ years | 3.256 | 0.462 | 7.05 | 0.000*** | 2.351 | 4.162 |
| Education: Level 2 | 0.259 | 0.380 | 0.68 | 0.495 | -0.486 | 1.005 |
| Education: Level 3 | 0.788 | 0.379 | 2.08 | 0.038** | 0.045 | 1.530 |

*Source: Opinium, Cebr analysis*

The above coefficients are in log-odd form and therefore not yet easily interpretable. Below is the calculated average marginal effect, which measures the average change in the predicted probability of employment from a one-unit change in our digital skills index. This is an easier variable to interpret.

Table 9: Average marginal effect of our logistic regression on employment

| Number of observations: 1,287 | | | | | | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | Standard Error | Z value | p-value | [95% Confidence Interval] | |
| Index score | 0.0002903 | 0.0001044 | 2.01 | 0.045** | 0.00004 | 0.00041 |

*Source: Opinium, Cebr analysis*

As can be seen, the coefficient on index score is of 0.0002093, meaning that on average, a 1-point increase in digital skills increases the probability of employment by 0.021 percentage points.

It is worth noting that our McFadden pseudo R-squared, while not below 10% is slightly low, at 15.27%. Nevertheless, our Wald Chi-squared statistic is large, of 79.81, indicating that our predictors are highly significant and contribute strongly to the model.

## Wider economy impacts

In the calculation of wider economy impacts, we have primarily focused on the impact of employees in the labour force learning to do all 20 tasks. We also briefly considered in our report the case in which everyone below the median is brought up to it, that is, learns to do 19 Work Essential Digital Skills tasks.

When comparing the wider economy impacts of learning 19 tasks as opposed to learning 20 tasks, we see that earnings in the latter would be higher by approximately £600 million. The intuition behind this may not be that learning to do one more digital task when already highly skilled has a large impact on earnings, but rather that other characteristics associated with being able to do all 20 tasks are driving this difference.

As mentioned above, a possible omitted variable in our analysis is advanced digital skills. It could be the case that moving from 19 to 20 tasks captures, not only being able to do one more fundamental Work Essential Digital Skills but also being able to do more advanced digital tasks such as coding (assuming that people with advanced skills would already be able to do all 20 tasks).

**For more information, please visit**


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