Digital Poverty in the UK: Analysis of Secondary Data

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Executive Summary

This report presents findings of digital poverty in the UK by analysing two datasets from each of two sources:

- First, two OFCOM surveys, each of over 3,000 respondents[1];
- Second, two Labour Force Survey (LFS) datasets from the Office for National Statistics (ONS), before and during the Covid-19 pandemic (Covid), each of over 68,000 respondents[2].

Results confirm the association of digital poverty with deprivation[3]. Various factors are identified to be associated with digital poverty in the UK such as:

1. Age;
2. Lack of confidence in reading and writing;
3. Lower socio-economic classification;
4. Disability;
5. Lower housing tenure;
6. Lack of qualifications;
7. More than one person in household;
8. Urban rather than rural; and
9. Ethnic minority.

Digital poverty increases almost exponentially with age: over 65s suffer much more digital poverty than younger age groups and digital poverty rises steeply even after 70 Lack of reading and writing is a major predictor of digital poverty among young people aged 16-24. Another important finding is a lack of motivation for having the Internet[4]. Comparing data during and before Covid, the results indicate that Covid disproportionately affected more disadvantaged groups in that those of lower socio-economic classification (SEC) and disabled suffered more digital poverty during Covid than before.

A number of factors affect the strength of the association of the above variables. These moderators change the association between the factors above and digital poverty and are central to our findings:

1. Lack of qualifications is associated with digital poverty more in the North than in the South of the UK;
2. Age is much more strongly associated with digital poverty for those living in rented accommodation rather than owned;
3. Lack of qualifications is more strongly associated with digital poverty for rural rather than urban residents;
4. Age is more strongly associated with digital poverty for females than males;
5. For ethnic minorities, disability is much more strongly associated with digital poverty than for the white majority.

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[1] OFCOM Adults Knowledge and Understanding survey 2021, number of respondents (n) = 3,095; and OFCOM Media Literacy CATI Omnibus survey, 2021, n = 3,143.

[2] Labour Force Survey (LFS), January – March 2019, n = 68719 (before the Covid-19 pandemic); and LFS January – March 2021, n = 68656 (during Covid). These specific tranches of LFS were selected as including the variables of interest.

[3] Ministry of Housing, Communities and Local Government, IOMD 2019, available from https://app.powerbi.com/view?r=eyJrIjoiOTdjYzIyNTMtMTcxNi00YmQ2LWI1YzgtMTUyYzMxOWQ3NzQ2IiwidCI6ImJmMzQ2ODEwLTljN2QtNDNkZS1hODcyLTI0YTJlZjM5OTVhOCJ9 Accessed 28 May 2022.

[4] Office for National Statistics (2019). Exploring the UK's digital divide, file:///C:/Users/akiko1/Downloads/Exploring%20the%20UK%20s%20digital%20divide.pdf Accessed 22 November 2021

Digital poverty has an impact on productivity that is even greater during than before Covid, and people in digital poverty tend to be in lower-paid jobs both during and before Covid. The findings reveal that people in London, Southeast and Southwest regions are suffering less from digital poverty than the rest of the UK. The main challenges associated with tackling digital poverty are discussed followed by our recommendations to overcome those issues.

Contents

Introduction and background

The topic has been close to the heart of our team for many years[5], with research into digital technologies, consumer behaviour and specifically how digital poverty relates to social exclusion and consumer wellbeing for over two decades. Back in 2007, Prof. Dennis wrote that 'The Internet has limited potential to compensate for shopping deserts, as consumers who do not have a good range of physical shops within walking distance also tend to lack access to the Internet (p143[6]). Papers in 2016[7], 2017[8],[9],[5] and 2022[10] present empirical evidence demonstrating the role of digital technologies in building consumer wellbeing and ameliorating social exclusion. Yet little has changed: 77% of over-70s have little online engagement; socially excluded groups are least likely to be able to use online services; virtually every service and government department ignored those suffering from digital poverty during lockdown[11],[12],[13]. In short, digital poverty has adverse effects on consumer wellbeing, and feeds social exclusion, with all the individual and social issues that this entails.

This report addresses the following research questions by means of an analysis of secondary data:

1. What are the main drivers of digital poverty in (areas/ regions of) the UK? How have these changed, or not, with the COVID-19 pandemic?
2. What are the impacts of digital poverty upon productivity and skills?
3. What communities are most severely affected by digital poverty, and how do impacts vary across and within communities?
4. What are the challenges associated with tackling digital poverty in the UK? What are the social, economic and cultural barriers to addressing digital poverty and how can they be effectively and equitably overcome?

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[5] Dennis C, Kent A, King T, Cohen G and Harris L (2002) 'E-retail and the consumer: 'shopping deserts issues' The 2002 Annual Manchester Conference for Contemporary Issues in Retail Marketing. Retailing for Communities: Issues of Inclusion and Exclusion, Manchester Metropolitan University.

[6] Dennis, C., Jayawardhena, C., Wright, L. T., & King, T. (2007). A commentary on social and experiential (e-)retailing and (e-)shopping deserts. International Journal of Retail and Distribution Management, 35(6), 443–456.

[7] Dennis, C., Alamanos, E., Papagiannidis, S., & Bourlakis, M. (2016). Does social exclusion influence multiple channel use? The interconnections with community, happiness, and well-being. Journal of Business Research, 69(3), 1061–1070.

[8] Dennis, C., Bourlakis, M., Alamanos, E., Papagiannidis, S., & Brakus, J. J. (2017). Value Co-Creation Through Multiple Shopping Channels: The Interconnections with Social Exclusion and Well-Being. International Journal of Electronic Commerce, 21(4), 517–547.

[9] Papagiannidis, S., Bourlakis, M., Alamanos, E., & Dennis, C. (2017). Preferences of smart shopping channels and their impact on perceived wellbeing and social inclusion. Computers in Human Behavior, 77, 396–405.

[10] Papagiannidis, S., Alamanos, E., Bourlakis, M., & Dennis, C. (2022). The pandemic consumer response: A stockpiling perspective and shopping channel preferences. British Journal of Management.

[11] Good Things Foundation. (2021). A blueprint to fix the digital divide, available from https://www.goodthingsfoundation.org/insights/a-blueprint-to-fix-the-digital-divide, Accessed 22 November 2021.

[12] Lloyds Bank. (2021). Lloyds Bank UK Consumer Digital Index 2021, available from https://www.lloydsbank.com/banking-with-us/whats-happening/consumer-digital-index.html, Accessed 22 November 2021.

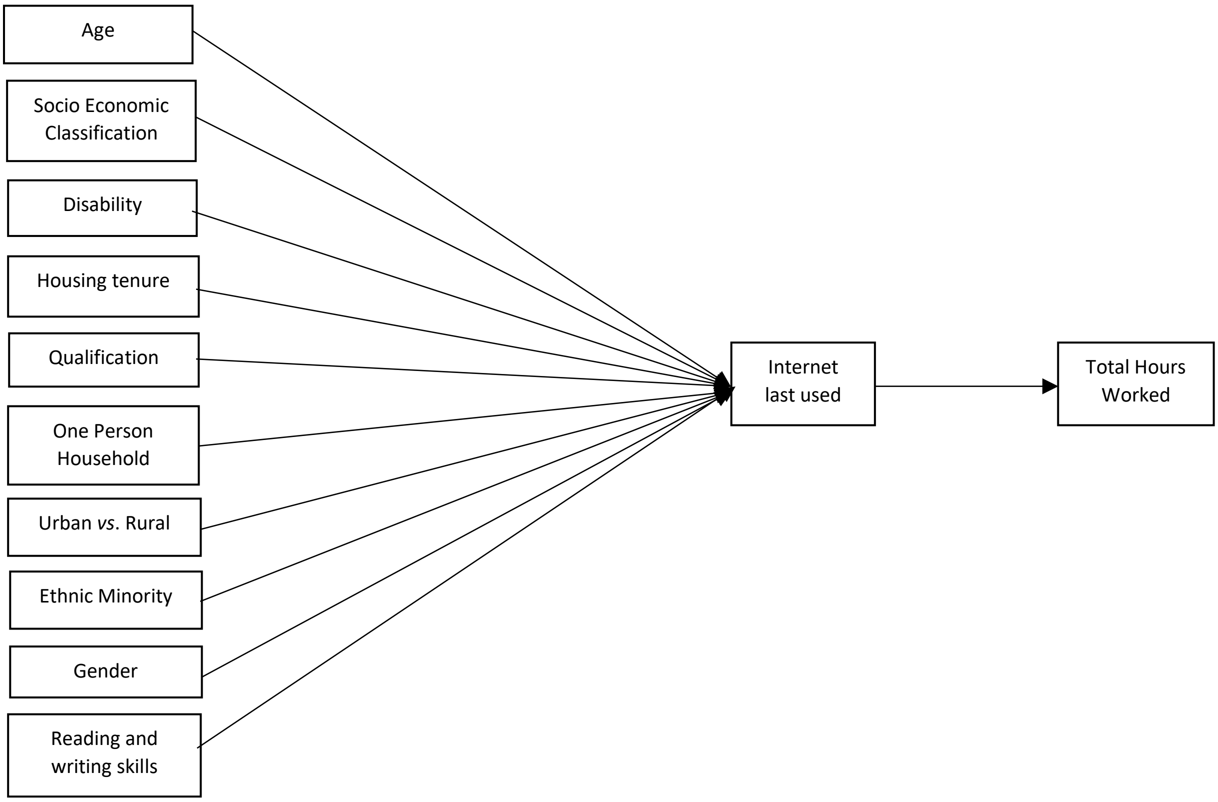
[13] Lloyds Bank. (2021). Lloyds Bank Essential Digital Skills Report 2021, available from https://www.lloydsbank.com/banking-with-us/whats-happening/consumer-digital-index.html, Accessed 22 November 2021.

Method

Digital poverty can be understood and defined in multiple ways. We consider as a basic measure, Internet non-users who have never used the Internet, or have not used the Internet for more than three months[14]. Notwithstanding, we discuss and comment on a range of measures including not having the skills and/ or resources to access the Internet or carry out other digital tasks.

To answer research questions (RQs) 1 and 2, we test a conceptual model (see Figure 1) of the antecedents of digital poverty. For RQ1, relevant factors include household income, education, socio-economic classification based on occupation type, disability, age, and single person *vs* multiple households. We use, variously, multiple regression, discriminant analysis, ANOVA (using the IBM SPSS statistics software) and path analysis (using the IBM SPSS AMOS program). For RQ2, we use hours worked as a proxy for productivity.

Figure 1. Conceptual model



[14] Office for National Statistics (2019). Exploring the UK's digital divide, https://www.ons.gov.uk/peoplepopulationandcommunity/householdcharacteristics/homeinternetandsocialmediausage/articles/exploringtheuksdigitaldivide/2019-03-04 Accessed 22 November 2021

We use two datasets from OFCOM, both of more than 3,000 respondents, collected from online surveys but with additional face-to-face surveys to capture responses from those respondents who lack access to the Internet. These datasets are useful because they contain, respectively, respondents' confidence in reading and writing, and respondents' stated reasons for not having the Internet at home. We also use datasets from the Office for National Statistics (ONS), *viz*, two editions of the Labour Force Survey (LFS), the largest UK household survey, each over 68,000 responses, one before the Covid-19 pandemic (January to March 2019) and one during (January to March 2021). The LFS datasets are useful in that their larger size means that smaller effects can be demonstrated to be statistically significant. Also, they are collected by telephone and face-to-face survey, which means that digital poverty is more accurately represented than in the OFCOM datasets.

Factors that may affect the relationships between the above concepts and digital poverty (moderators) include gender, ethnicity, household tenure, urban/ local, and/ or geographic region. These relationships are explored by comparing the segments (multi-group analyses) using IBM SPSS AMOS path analysis. We also use the Index of Multiple Deprivation (IOMD 2019) from the Ministry of Housing, Communities and Local Government, to demonstrate the correlation of digital poverty with deprived local authority areas. The confirmed models answering RQ1 and 2 provide the basis for answering RQ3 and 4. All datasets contain different variables. The composite results reported in the Executive Summary combine the findings from the various datasets as far as practicable. All datasets closely match UK average demographics. They are therefore used unweighted in order to simplify interpretation of results for comparative demographics. Most variables are non-normally distributed. Statistical significance is therefore established by examining 1,000 subsamples (for the OFCOM data, 2,000 for ONS), in order to evaluate the reliability of the findings (bootstrapping) except where stated. Path analyses use the correlations between variables as the input because the secure ONS raw data is not available for analysis by SPSS AMOS structural equation modelling.

Findings

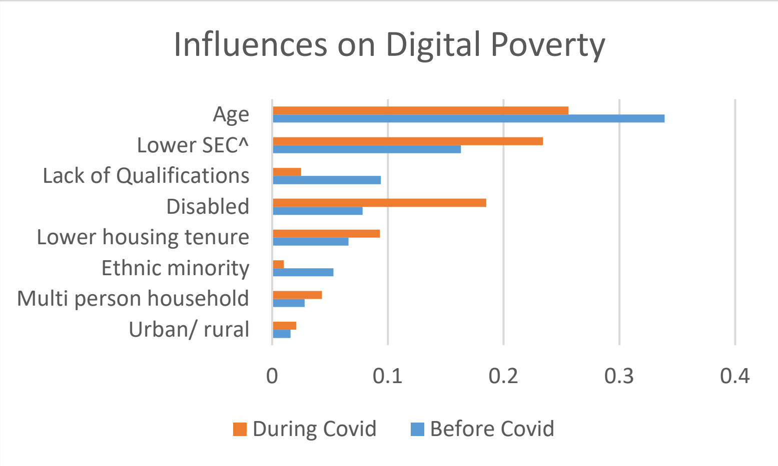
1. What are the main drivers of digital poverty in (areas/regions of) the UK? How have these changed, or not, with the COVID-19 pandemic?

Looking into both datasets from OFCOM and ONS (both before and during Covid), we find that factors strongly associated with digital poverty (in approximate ranked order) are (1) age, (2) lack of confidence in reading and writing[15], (3) lower socio-economic classification, (4) disability, (5) lower housing tenure[16], and (6) lack of qualifications. The following factors are found to be weakly associated with digital poverty: (7) more than one person in household, (8) urban rather than rural, and (9) ethnic minority. See Figure 2.

These associations do not prove causation. In some cases, the reverse can be the case, for example, digital poverty may cause lower economic achievement and thus lower household tenure. Low household income is also strongly associated with digital poverty, but we do not include this variable in our model as we expect that digital poverty causes lower productivity, making the argument circular.

[15] The factor was available only in OFCOM datasets. Please see Table 3.
[16] Measured from owned outright is the highest and squatting is the lowest.

Figure 2. Relative strength of predictors of low use of Internet, before and during Covid



Note: Effect of variable on digital poverty, 0-1 scale (standardised path coefficients). Derived from ONS data.
^ SEC = socio-economic classification.

We compared those factors before and during Covid using ONS datasets, and found that disability, lower socio-economic classification and lower housing tenure have a stronger association with digital poverty during Covid. We observed marginally stronger association during Covid between more than one person in household and digital poverty. Age, lack of qualifications, and ethnic minority demonstrated a weaker association with digital poverty during Covid. The association between urban rather than rural with digital poverty was similar before and during Covid. Please see Table 1 below for the results of the path analysis based on the ONS results.

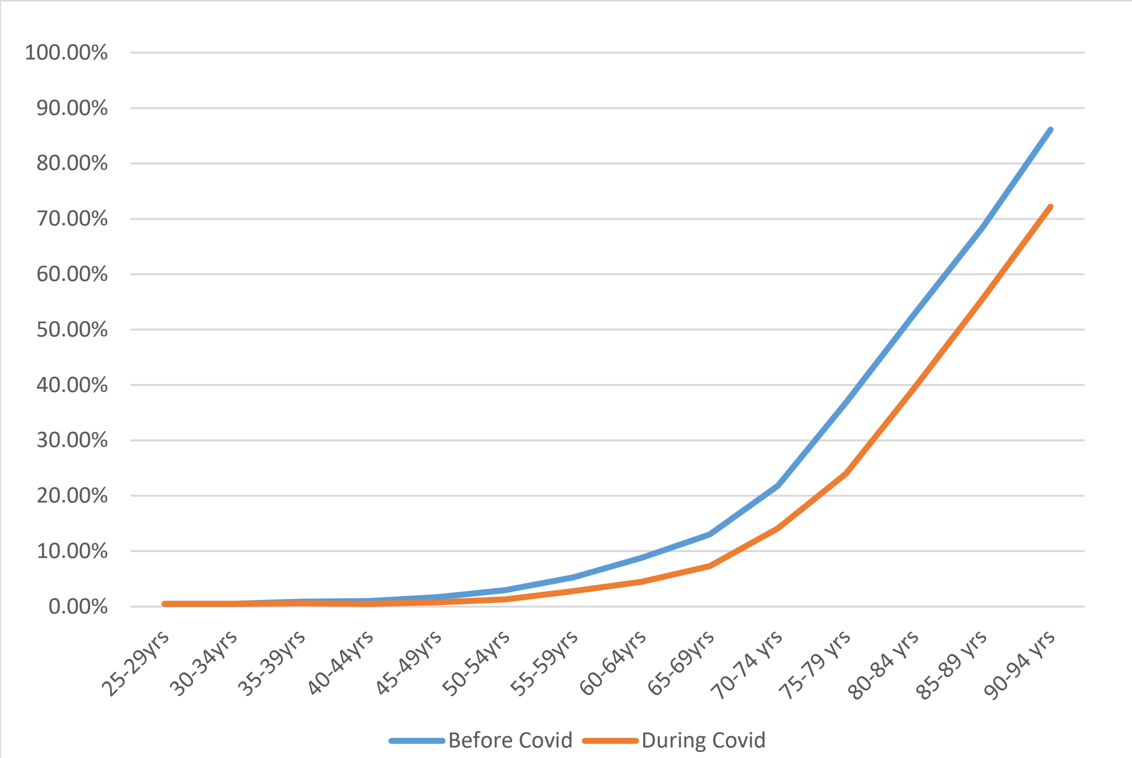
Table 1. Path analysis comparing predictors of low use of Internet and association of low use of Internet with hours worked in the previous week before *vs* during Covid.

Path	Compared to before Covid, the effect is greater (or less) during Covid by (rescaled 0-100) [1]	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
to time from when last Internet used		Before Covid n=68719	During Covid n=68656	
Disabled	**10.7**	0.078 (21.4)	0.185 (47.6)	297.6
Lower SEC^	**7.1**	0.163 (41.1)	0.234 (54.6)	60.7
Lower housing tenure	**2.7**	0.066 (17.4)	0.093 (24.6)	21.8
Multi person household	**1.5**	0.028 (7.9)	0.043 (11.7) **	4.9 *
Age	**(-8.3)**	0.339 (85.0)	0.256 (62.6)	410.3
Lack of Qualifications	**(-6.9)**	0.094 (24.0)	0.025 (6.04)	171.2
Ethnic minority	**(-4.3)**	0.053 (15.1)	.010 (2.9)	71.2
Urban/ rural	No significant change	0.016 (4.7)	.021 (6.1)	0.1 ns
Last Internet Used → Hours worked	**1.4**	-0.023 (6.0)	-0.037 (9.7) **	12.6

Datasets used: LFS (a) January – March 2019; (b) January – March 2021.
^ SEC = socio-economic classification
Overall chi square 902.7 (10df). Path coefficients and differences significant at 99.9% confidence except where stated: ** = 99%; * = 95%; ns = non-significant. df = degrees of freedom, ns = non-significant. Significance testing of path coefficients is by Bootstrapping/ Monte Carlo as the variables are not normally distributed.
[1] Difference between standardised path coefficients, multiplied by 100.

Digital poverty increases almost exponentially with age, such that age is much more associated with digital poverty for over 65s than for other age categories, and steeply increases even after age 70 (Figure 3 and Table 2). On the other hand, digital poverty reduced during Covid, especially for over-65s.

Figure 3. Digital Poverty Index# by Age Categories – During and Before Covid



0 = no digital poverty, i.e. all respondents would have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

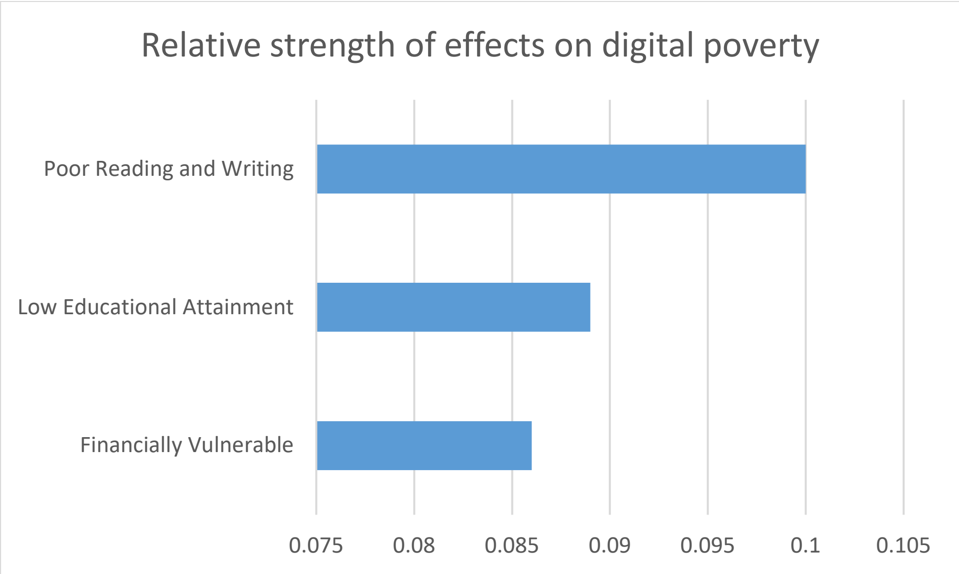
Table 2. Digital Poverty Index # by Age Categories – During and Before Covid

	During Covid		Before Covid	
Age Band	Number of responses	**Digital Poverty Index #**	Number of responses	**Digital Poverty Index #**
Age 16-24	4712	**0.31**	5911	**0.58**
Age 25-65	35419	**1.25**	38304	**2.08**
Age 66-99	16593	**12.54**	12454	**18.46**
Total	56724	**4.47**	56669	**5.52**

0 = no digital poverty, i.e. all respondents would have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

In our modelling, for every one person in digital poverty, there are three people who are not in digital poverty, and both groups (digital poverty and non-digital poverty) are in similar age range and face similar resources challenges such as financial vulnerability arising from low income, often with more children to support[17]. The main reasons that respondents state for not having Internet at home concern lack of interest, complexity and security. Costs and broadband connectivity come some way behind[18]. The main causes of digital poverty, at least for people young enough to be economically active, tend to arise from lack of confidence in reading/ writing, low educational attainment, motivation and attitude factors (which are more prevalent in lower-resources groups) rather than directly from income/ cost issues (please see Figure 4, Tables 3 and 4 below).

Figure 4. Relative strength of effects on digital poverty



Dataset: OFCOM Adults Knowledge and Understanding Survey 2021.
This dataset is useful in containing responses on confidence in reading and writing
Number of respondents (n) = 3,095. Coefficients are statistically significant at 99% confidence. Adjusted R^2 = 0.042. The highest variance inflation factor (VIF) is 1.05, indicating that co-linearity is not an issue. The relative strengths of effects on digital poverty are standardised regression coefficients (0-1 scale).

Table 3. Linear multiple regression

Dependent variable: low hours spent online	Relative strength of effects on digital poverty
1. Poor Reading and Writing	0.100
2. Low Educational Attainment	0.089
3. Financially Vulnerable	0.086

Dataset: OFCOM Adults Knowledge and Understanding Survey 2021.
This dataset is useful in containing responses on confidence in reading and writing
Number of respondents (n) = 3,095. Coefficients are statistically significant at 99% confidence. Adjusted R^2 = 0.042. The highest variance inflation factor (VIF) is 1.05, indicating that co-linearity is not an issue. The relative strengths of effects on digital poverty are standardised regression coefficients (0-1 scale).

Young people (aged 16-24) with low or zero hours spent online are significantly more likely to lack confidence in reading and writing than are older people (99% confidence). There is a significant

[17] See footnote 1
[18] See footnote 1

positive association between reading/ writing and age, meaning that older people are more confident in reading and writing[19]. Of those who use the Internet less than two hours per week, **none** of the 16–24-year-olds in the sample are even 'fairly' confident in reading/ writing.

Table 4. Stated reasons for not having Internet at home

Reasons stated for having no Internet at home	Percent of respondents
No need/ not interested	47
Too complicated	22
Security/ fraud/ privacy	22
Someone else can go online for me	20
Monthly cost of broadband too high	8.5
Broadband set up costs too high	8.0

Dataset: OFCOM Media Literacy CATI Omnibus survey, 2021, n = 3,143. This dataset is useful in containing responses on respondents' reasons for having no Internet at home; 200 respondents (6.4%) have no Internet at home (189 stated a reason).
The demographic profiles are similar across all the reasons for not using the Internet except that older people cite 'too complicated' (or 'too complicated and too expensive') significantly more than others (99% confidence, F = 4.811 (3); Age skewness = 0.022, kurtosis = -1.33 (justifying the parametric test).

A model based on age, lower socio-economic classification, number of people in the household and financial vulnerability classifies 74% of those with no Internet at home into the target group, although people with no Internet at home make up only 23% of that group. Hence, for every one person with no Internet at home with the age and resources challenges, there are three people with similar challenges who do have Internet at home[20]. As people with no Internet at home mostly state reasons such as no need/ not interested, too complicated, security/ fraud/ privacy, and someone else can go online for me, it appears that the main reasons why those two sub-groups are facing similar challenges but one has internet and the others not concern motivation, complexity and security rather than income or costs.

Factors that Influence the Strength of the Effect of Other Factors (Moderators)

There are many factors that influence the strength of the effect of other factors on digital poverty (significant moderations), some of which (discussed below) are central to our findings. As already noted, age was much more associated with digital poverty before compared to during Covid. This finding suggests that many older people may have taken a step towards digital inclusion to help cope with lockdown. On the other hand, disability and lower socio-economic classification (SEC) were much more associated with digital poverty during Covid than before Covid, suggesting that Covid hit those more-disadvantaged groups proportionally harder than others.

Other influences that are strong and meaningful include, for example, that lack of qualifications is associated with digital poverty more in the North than in the South of the UK. The influence of lower SEC on digital poverty is slightly greater in the North than in the South of the UK. The influence of living in rented (rather than owned) accommodation on digital poverty is greater in the south than in the north of the UK (but less so during Covid). Figure 5a/ b below illustrates the path analyses comparing predictors of low use of Internet, detailed in Table 5a/ b, which also includes association between low use of Internet and hours worked in the previous week, comparing London and the south of England with other areas of the UK.

[19] For the sample overall, chi-square = 155 (1), 99.9% confidence by Monte Carlo.
[20] Discriminant analysis followed by automatic binning.

Figure 5a. Relative strength of predictors of low use of Internet, North *vs* South During Covid.

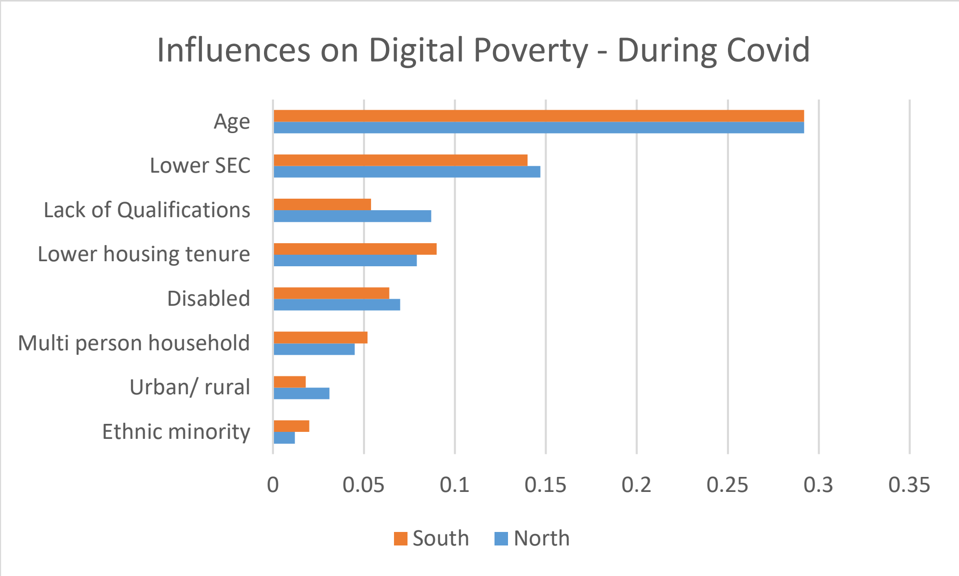


Figure 5b. Relative strength of predictors of low use of Internet, North *vs* South Before Covid.

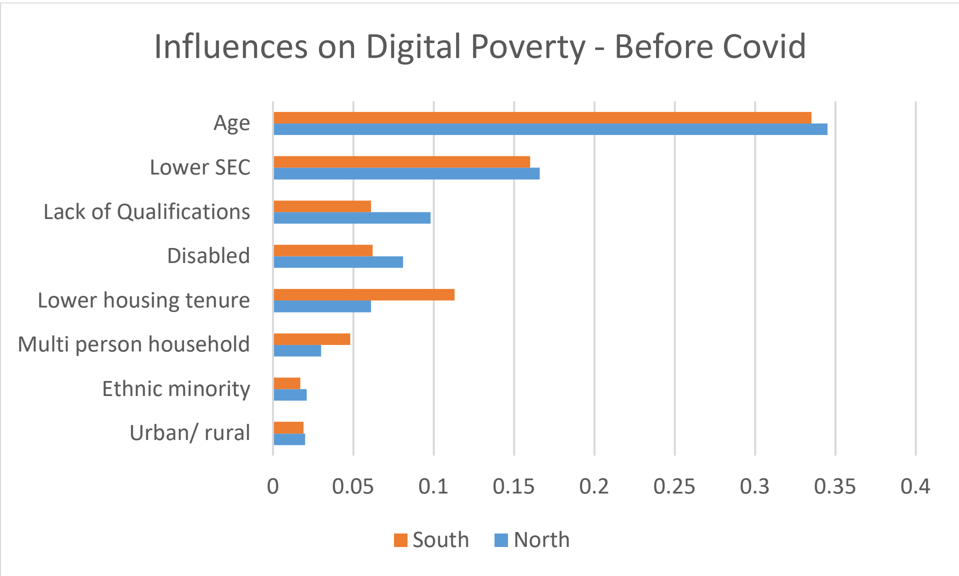


Table 5a. Relative strength of predictors of low use of Internet, North *vs* South During Covid.

Path to time from when last Internet used	Compared to the South, the effect is greater (or less) in the North by (rescaled 0-100) #	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
		North n=37,848	South n=18,832	
Lack of Qualifications	**3.3**	0.087 (18.0)	0.054 (7.7)	29.1
Urban/ rural	**1.3**	0.031 (7.3)	0.018 (2.8) **	4.9 *
Lower SEC ^	**0.7**	0.147 (29.8)	0.140 (19.6)	19.4
Age	**0**	0.292 (58.8)	0.292 (40.1)	53.5
Disabled	No significant difference	0.070 (15.3)	0.064 (9.9)	3.6 ns
Lower housing tenure	No significant difference	0.079 (16.8)	0.090 (13.1)	0.8 ns
Multi person household	No significant difference	0.045 (9.9)	0.052 (7.8) **	0.2 ns
Ethnic minority	No significant difference	0.012 (2.9) *	0.020 (3.1) **	.02 ns
Last Internet Used → Hours worked	**(-1.6)**	-0.033 (7.1)	-0.049 (7.4)	8.7 **

Overall delta chi square 209.4 (10df).

Table 5b. Relative strength of predictors of low use of Internet, North *vs* South Before Covid.

Path to time from when last Internet used	Compared to the South, the effect is greater (or less) in the North by (rescaled 0-100) #	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
		North n=39,236	South n=17,433	
Lack of Qualifications	**3.7**	0.098 (20.9)	0.061 (8.6)	39.1
Age	**1.0**	0.345 (71.2)	0.335 (45.5)	68.1
Disabled	**1.9**	0.081 (15.3)	0.062 (9.4)	13.8
Lower SEC ^	**0.6**	0.166 (34.8)	0.160 (22.1)	23.0
Lower housing tenure	**(-5.2)**	0.061 (13.2)	0.113 (15.9)	17.4
Multi person household	No significant difference	0.030 (6.8)	0.048 (7.3) **	1.9 ns
Urban/ rural	No significant difference	0.020 (4.9) **	0.019 (3.0) **	0.2 ns
Ethnic minority	No significant difference	0.021 (5.1)	0.017 (2.7) **	3.6 ns
Gender	No significant difference	ns	-0.014 (2.2) *	2.1 ns
Last Internet Used → Hours worked		-0.022 (4.8)	-0.027 (3.9)	1.4 ns

Overall delta chi square 326.5 (10df).
Path coefficients and differences significant at 99.9% confidence except where stated: ** = 99%; * = 95%; ns = non-significant.
df = degrees of freedom, ns = non-significant. Significance testing of path coefficients is by Bootstrapping/ Monte Carlo as the variables are not normally distributed.
^ SEC = socio-economic classification
# Difference between standardised path coefficients, multiplied by 100.

Age is much more strongly associated with digital poverty and lower SEC is slightly more associated with digital poverty for those living in rented accommodation rather than owned. On the other hand, disability and lack of qualifications are more associated with digital poverty for those living in owned accommodation rather than rented. Figure 6a/ b below exhibits the path analyses comparing predictors of low use of Internet, detailed in Table 6a/ b, which also includes association between low use of Internet and hours worked in the previous week, comparing those living in owned accommodation with those in rented and other types of accommodation.

Figure 6a. Relative strength of predictors of low use of Internet, Housing Tenure During Covid.

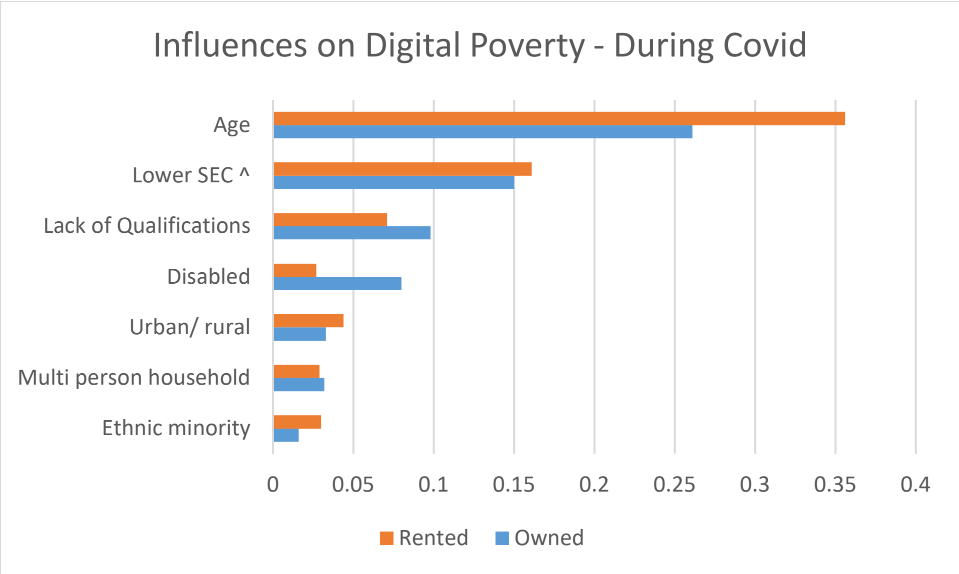


Figure 6b. Relative strength of predictors of low use of Internet, Housing Tenure Before Covid.

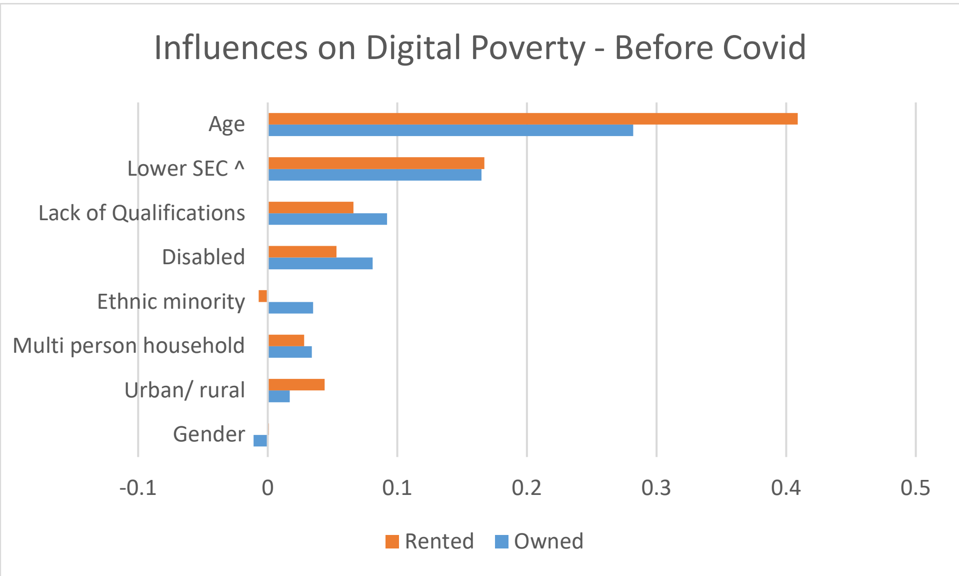


Table 6a. Relative strength of predictors of low use of Internet, Housing Tenure During Covid

Path to time from when last Internet used	Compared to Rented, the effect is greater (or less) in Owned housing by (rescaled 0-100) [1]	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
		Owned n=53,316	Rented n=14,309	
Age	**(-9.5)**	0.261 (56.4)	0.356 (43.0)	58.8
Lower SEC ^	**(-5.5)**	0.150 (30.3)	0.161 (18.7)	21.0
Disabled	**5.3**	0.080 (17.7)	0.027 (3.4)	4.4 *
Lack of Qualifications	**2.7**	0.098 (20.3)	0.071 (8.3)	36.3
Multi person household	No significant difference	0.032 (7.0)	0.029 (3.6)	0.02 ns
Urban/ rural	**(-5.5)**	0.033 (7.7)	.044 (5.8) ns	4.6 *
Ethnic minority	No significant difference	0.016 (3.8)	.030 (1.8) **	.02 ns
Last Internet Used → Hours worked	**(-1.8)**	-0.033 (7.1)	-0.051 (6.1)	8.7 **

Overall delta chi square 227.9 (9 df).

Table 6b. Relative strength of predictors of low use of Internet, Housing Tenure Before Covid

Path to time from when last Internet used	Compared to Rented, the effect is greater (or less) in Owned housing by (rescaled 0-100) [#]	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
		Owned n=47,626	Rented n=21,057	
Age	**(-12.7)**	0.282 (61.5)	0.409 (61.6)	513.3
Lower SEC ^	**(-0.2)**	0.165 (34.3)	0.167 (24.7)	21.3
Disabled	**2.8**	0.081 (18.4)	0.053 (8.2)	10.5 *
Lack of Qualifications	**2.6**	0.092 (19.6)	0.066 (9.8)	4.3 *
Multi person household	No significant difference	0.034 (7.8)	0.028 (4.4)	0.005 ns
Urban/ rural	**(-2.7)**	0.017 (4.1)	.044 (4.7)	6.8 *
Ethnic minority	**4.2**	0.035 (8.2)	-.007 (1.2) ns	36.6
Gender	No significant difference	-0.011 (2.6) **	0.001 (0.2) ns	2.2 ns
Last Internet Used → Hours worked	No significant difference	-0.020 (4.4)	-0.031 (4.5)	0.6 ns

Overall delta chi square 684.5 (9 df).
Path coefficients and differences significant at 99.9% confidence except where stated: ** = 99%; * = 95%; ns = non-significant.
df = degrees of freedom, ns = non-significant. Significance testing of path coefficients is by Bootstrapping/ Monte Carlo as the variables are not normally distributed.
^ SEC = socio-economic classification
[#] Difference between standardised path coefficients, multiplied by 100.

Age is also more strongly associated with digital poverty for those living in urban rather than rural locations. On the other hand, lack of qualifications is more strongly associated with digital poverty for rural rather than urban residents during Covid (there was no significant difference before Covid). Figure 7a/ b below exhibits the path analyses comparing predictors of low use of Internet, detailed in Table 7a/ b, which also includes association between low use of Internet and hours worked in the previous week, comparing urban *vs* rural residence.

Figure 7a. Relative strength of predictors of low use of Internet, Rural *vs* Urban During Covid.

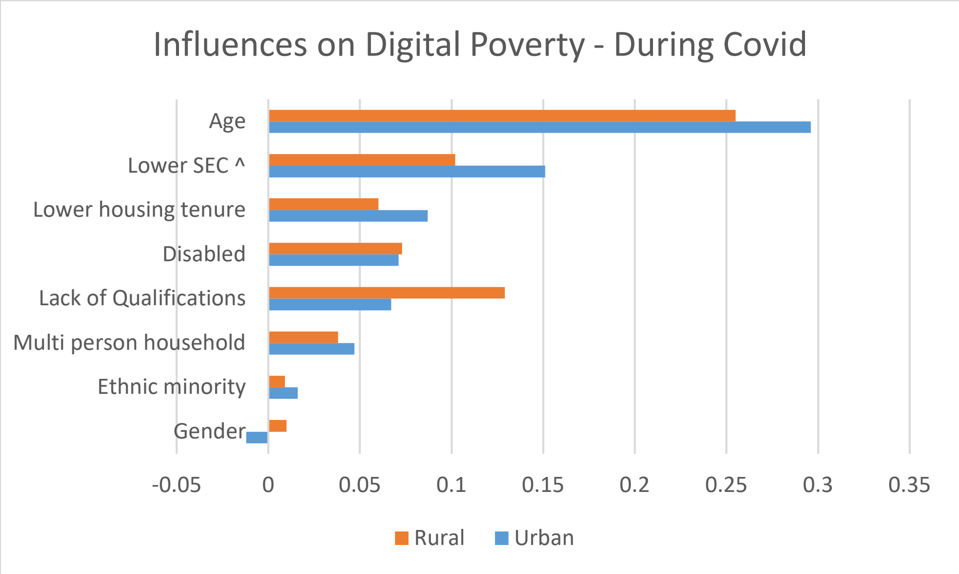


Figure 7b. Relative strength of predictors of low use of Internet, Rural *vs* Urban Before Covid.

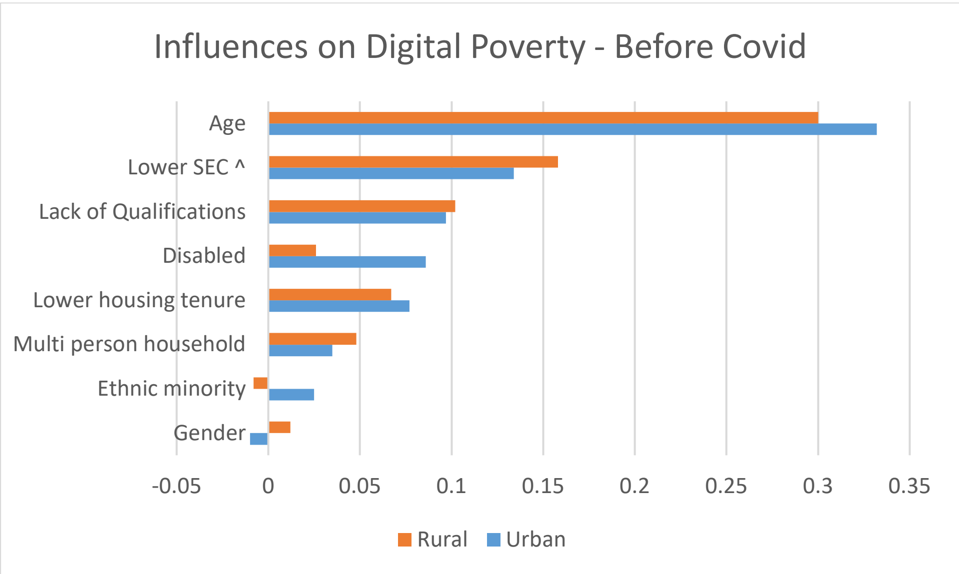


Table 7a. Urban vs rural During Covid.

Path to time from when last Internet used	Compared to Rural, the effect is greater (or less) in Urban areas by (rescaled 0-100) #	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
		Urban n=55,955	Rural n=8,803	
Age	**4.1**	0.296 (65.4)	0.255 (22.7)	24.4
Lower SEC ^	**4.9**	0.151 (33.5)	0.102 (9.1)	27.2
Disabled	No significant difference	0.071 (17.2)	0.073 (7.0)	0.02 ns
Lack of Qualifications	**(-6.2)**	0.067 (15.3)	0.129 (11.8)	22.9
Lower housing tenure	**2.7**	0.087 (20.6)	0.060 (5.6)	6.6 *
Multi person household	No significant difference	0.047 (11.5)	0.038 (3.6)	1.2 ns
Ethnic minority	No significant difference	0.016 (4.1)	0.009 (0.9) ns	.007 ns
Gender	**2.2**	-.012 (3.1) **	0.010 (1.0) ns	4.5 *
Last Internet Used → Hours worked	**3.1**	-0.045 (10.7)	-0.014 (1.3)	4.2 *

Overall delta chi square 84.3 (9df).

Table 7b. Urban vs rural Before Covid

Path to time from when last Internet used	Compared to Rural, the effect is greater (or less) in Urban areas by (rescaled 0-100) #	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
		Urban n=56312	Rural n=7,354	
Age	**3.2**	0.332 (72.9)	0.300 (24.6)	7.3 *
Lower SEC ^	No significant difference	0.134 (30.0)	0.158 (13.2)	1.9 ns
Disabled	**6.0**	0.086 (21.4)	0.026 (2.3) *	25.1
Lack of Qualifications	No significant difference	0.097 (22.3)	0.102 (8.6)	0.2 ns
Lower housing tenure	No significant difference	0.077 (18.0)	0.067 (5.6)	0.3 ns
One person household	No significant difference	-0.035 (8.7)	-.048 (4.3)	1.0 ns
Ethnic minority	No significant difference	0.025 (6.4)	-0.008 (0.9) ns	2.7 ns
Gender	No significant difference	-.010 (2.6)	0.012 (1.0) ns	3.6 ns
Last Internet Used → Hours worked	**2.8**	-0.031 (7.4)	-0.003 (0.3) ns	5.6 *

Urban vs rural defined from 2011 census classification (9-digit)

Overall delta chi square 55.6 (9df). Path coefficients and differences significant at 99.9% confidence except where stated: ** = 99%; * = 95%; ns = non-significant.

df = degrees of freedom, ns = non-significant. Significance testing of path coefficients is by Bootstrapping/ Monte Carlo as the variables are not normally distributed.

^ SEC = socio-economic classification

Difference between standardised path coefficients, multiplied by 100.

Gender has minimal effect on digital poverty except that age is much more strongly associated with digital poverty and urban (rather than rural) is slightly more associated with digital poverty for or females than males. Lack of qualifications has more influence on digital poverty for males rather than females. Figure 8a/ b below exhibits the path analyses comparing predictors of low use of Internet, detailed in Table 8a/ b, which also includes association between low use of Internet and hours worked in the previous week, comparing females and males.

Figure 8a. Relative strength of predictors of low use of Internet by Gender, During Covid.

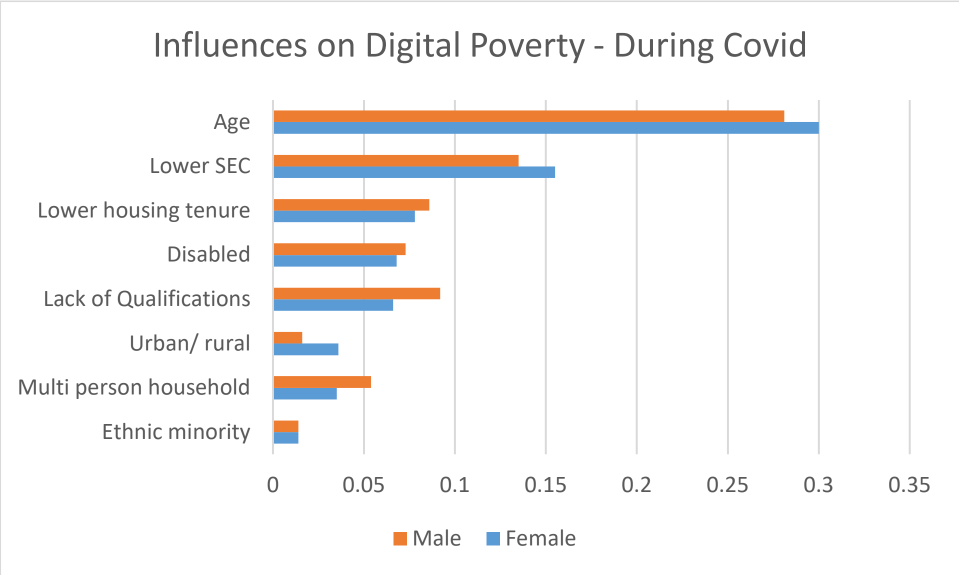


Figure 8b. Relative strength of predictors of low use of Internet by Gender, Before Covid.

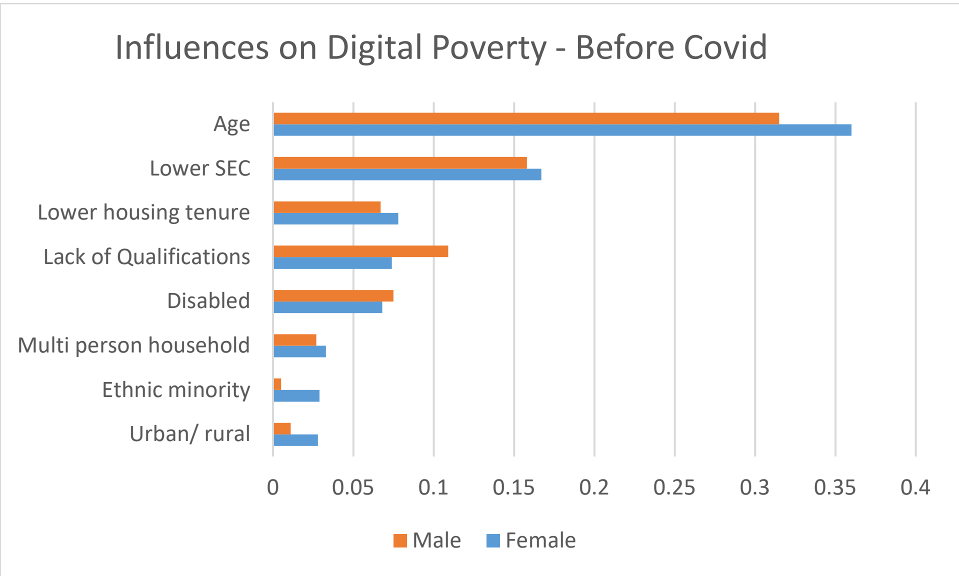


Table 8a. Female vs Male During Covid.

Path	Compared to Males, the effect is greater (or less) for females by (rescaled 0-100) #	Effect of variable, 0-1 scale, i.e. standardised path coefficients (t-values)		Difference between groups delta chi-square (1df)
to time from when last Internet used		Female n=35,908	Male n=32,746	
Age	**1.9**	0.300 (53.4)	0.281 (46.4)	22.7
Lower SEC	**2.0**	0.155 (27.5)	0.135 (22.9)	11.3 *
Disabled	No significant difference	0.068 (13.3)	0.073 (7.0)	0.8 ns
Lack of Qualifications	**(-2.6)**	0.066 (12.1)	0.092 (15.7)	22.9
Lower housing tenure	No significant difference	0.078 (14.5)	0.086 (15.4)	0.7 ns
Multi person household	**(-1.9)**	0.035 (6.9)	0.054 (9.6)	4.5 *
Urban/ rural	**2.0**	0.036 (7.4)	0.016 (3.0) **	9.2 **
Ethnic minority	No significant difference	0.014 (2.9) **	0.014 (2.6) **	.004 ns
Last Internet Used → Hours worked	No significant difference	-0.048 (9.1)	-0.039 (7.1)	0.5 ns

Overall delta chi square 70.5 (9df).

Table 8b. Female vs Male Before Covid.

Path	Compared to Males, the effect is greater (or less) for Females by (rescaled 0-100) #	Standardised path coefficient (t-values)		Difference between groups delta chi-square (1df)
to time from when last Internet used		Female n=35,838	Male n=32,871	
Age	**4.5**	0.360 (65.2)	0.315 (52.7)	60.7
Lower SEC	No significant difference	0.167 (30.4)	0.158 (27.4)	3.8 ns
Disabled	No significant difference	0.068 (15.5)	0.075 (14.1)	0.004 ns
Lack of Qualifications	**(-3.5)**	0.074 (13.7)	0.109 (19.0)	15.4
Lower housing tenure	No significant difference	0.078 (15.0)	0.067 (12.2)	3.7 ns
Multi person household	No significant difference	0.033 (6.7)	0.027 (5.0)	1.0 ns
Urban/ rural	**1.7**	0.028 (5.9)	0.011 (2.2) *	6.6 *
Ethnic minority	**2.4**	0.029 (6.0)	0.005 (1.0) ns	11.1 **
Last Internet Used → Hours worked	**3.1**	-0.049 (9.3)	-0.018 (3.3)	14.5

Overall delta chi square 109.7 (9df). Path coefficients and differences significant at 99.9% confidence except where stated: ** = 99%; * = 95%; ns = non-significant.

df = degrees of freedom, ns = non-significant. Significance testing of path coefficients is by Bootstrapping/ Monte Carlo as the variables are not normally distributed.

Difference between standardised path coefficients, multiplied by 100.

Similarly, ethnicity has only small effects on digital poverty except that for ethnic minorities, disability is much more strongly associated with digital poverty than for the white majority. Figure 9a/ b below exhibits the path analyses comparing predictors of low use of Internet, detailed in Table 9a/ b, which also includes association between low use of Internet and hours worked in the previous week, comparing ethnic minorities and white. These results paint a picture of a compound effect of disadvantages such as ethnicity and disability.

Figure 9a. Relative strength of predictors of low use of Internet Ethnic minority *vs* White, During Covid.

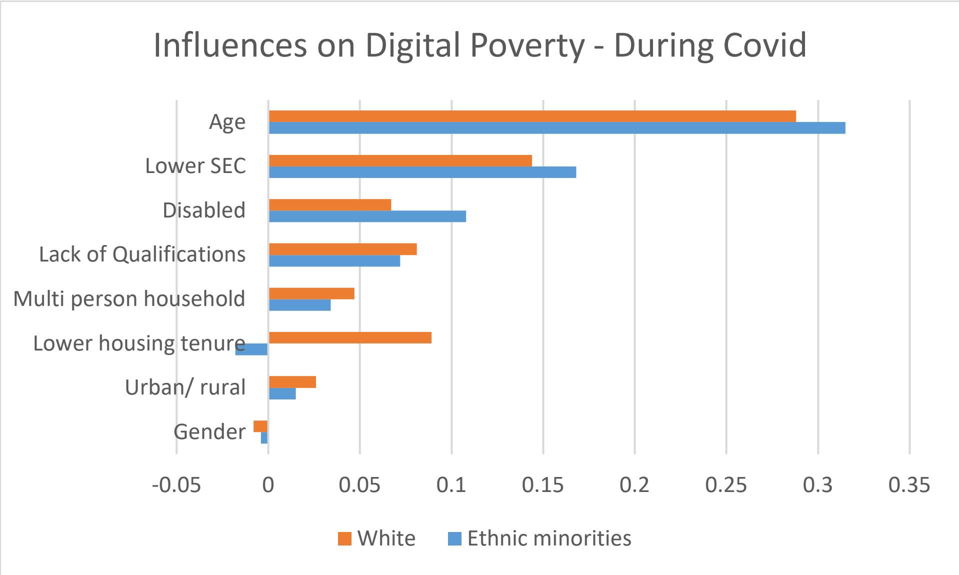


Figure 9b. Relative strength of predictors of low use of Internet Ethnic minority *vs* White, During Covid.

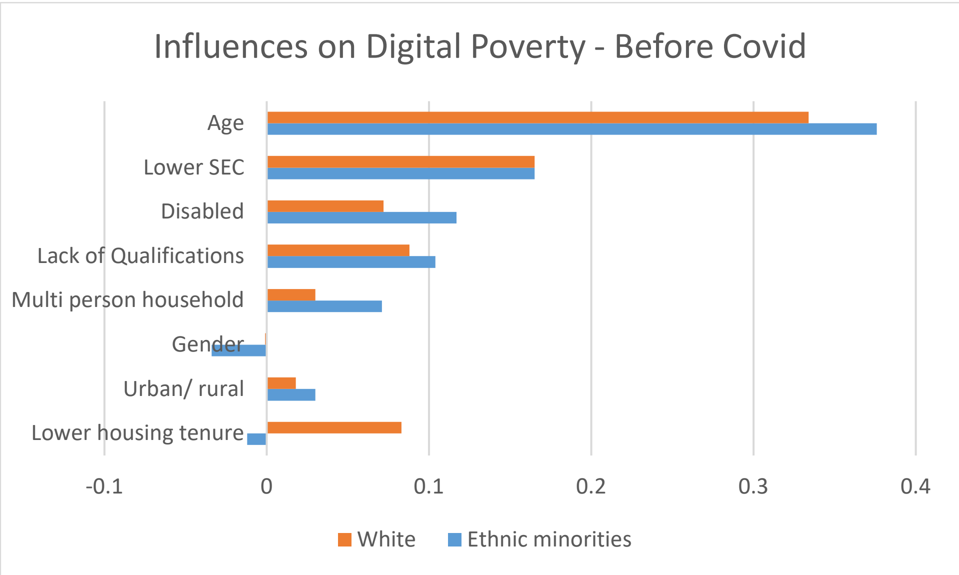


Table 9a. Ethnic minority *vs* White During Covid.

Path	Compared to the White majority, the effect is greater (or less) for Ethnic minorities by (rescaled 0-100) #	Standardised path coefficient (t-values)		Difference between groups delta chi-square (1df)
to time from when last Internet used		Ethnic minorities n=5,115	White n=63,274	
Age	No significant difference	0.315 (22.8)	0.288 (67.6)	0.3 ns
Lower SEC	No significant difference	0.168 (11.3)	0.144 (33.9)	0.1 ns
Disabled	**4.1**	0.108 (8.2)	0.067 (17.3)	7.1 **
Lack of Qualifications	No significant difference	0.072 (2.5)	0.081 (19.5)	3.7 ns
Lower housing tenure	**(-10.7)**	-0.018 (1.3) ns	0.089 (22.1)	81.9
Multi person household	No significant difference	0.034 (9.9) *	0.047 (12.0)	2.2 ns
Urban/ rural	No significant difference	0.015 (1.2) ns	0.026 (7.1)	0.007 ns
Gender	No significant difference	-0.004 (0.3) ns	-0.008 (2.1) *	0.1 ns
Last Internet Used → Hours worked	No significant difference	-0.012 (0.8) ns	-0.039 (9.8)	2.4 ns

Overall delta chi square 115.1 (9df).

Table 9b. Ethnic minority *vs* white Before Covid

Path	Compared to the White majority, the effect is greater (or less) for Ethnic minorities by (rescaled 0-100) #	Standardised path coefficient (t-values)		Difference between groups delta chi-square (1df)
to time from when last Internet used		Ethnic minorities n=7,014	White n=61,631	
Age	**4.2**	0.376 (32.1)	0.334 (78.4)	170.4
Lower SEC	**0**	0.165 (13.3)	0.165 (39.4)	49.8
Disabled	**4.5**	0.117 (10.4)	0.072 (18.6)	642.9
Lack of Qualifications	**1.6**	0.104 (8.6)	0.088 (21.1)	6.1 *
Lower housing tenure	No significant difference	-0.012 (1.1) ns	0.083 (20.3)	0.5 ns
Multi person household	**4.1**	0.071 (6.3) *	0.030 (7.8)	6.1 *
Urban/ rural	No significant difference	0.030 (2.9) **	0.018 (4.9)	0.9 ns
Gender	No significant difference	-0.034 (3.3) **	-0.001 (0.4) ns	1.3 ns
Last Internet Used → Hours worked	**(-0.1)**	-0.023 (1.9) ns	-0.024 (6.0)	12.9

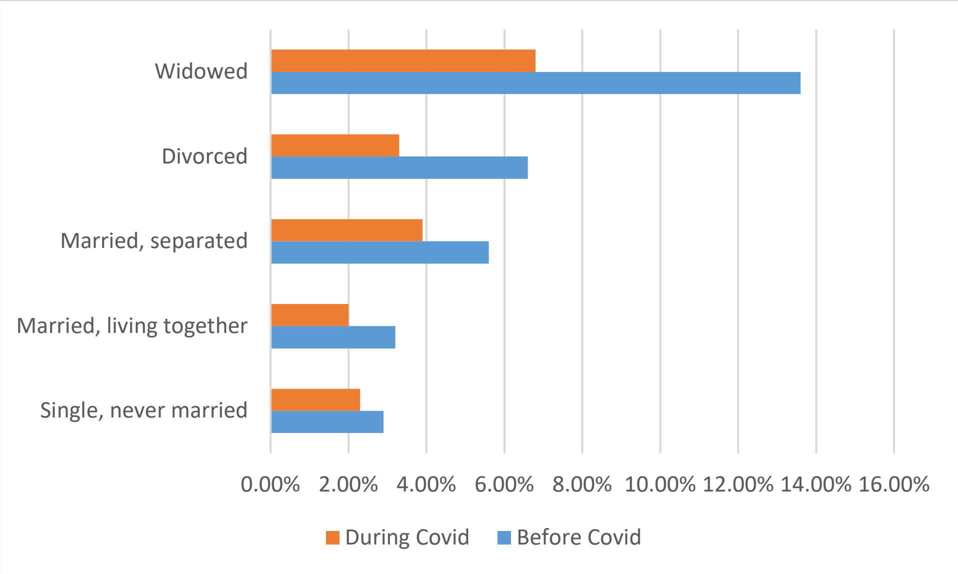
Overall delta chi square 1086.3 (9df). Path coefficients and differences significant at 99.9% confidence except where stated: ** = 99%; * = 95%; ns = non-significant.

df = degrees of freedom, ns = non-significant. Significance testing of path coefficients is by Bootstrapping/ Monte Carlo as the variables are not normally distributed.

Difference between standardised path coefficients, multiplied by 100.

There is little difference in digital poverty between single (never married) and married respondents under 70 years old, although digital poverty is higher for separated, divorced, and especially widowed individuals (Figure 10a and Table 10a).

Figure 10a. Digital Poverty Index# by Marital Status – During and Before Covid, under 70s



0 = no digital poverty, i.e. all respondents would have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

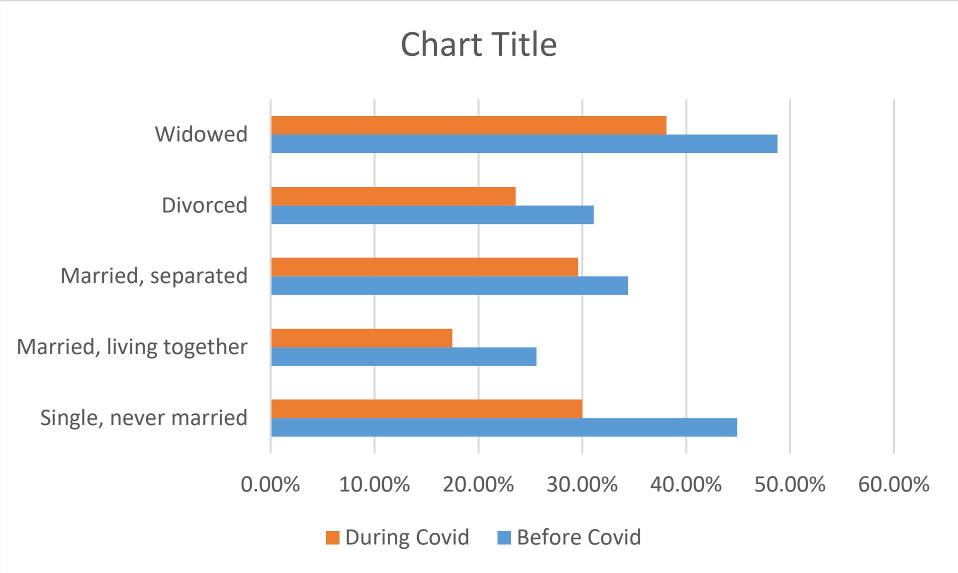
Table 10a. Digital Poverty Index# by Marital Status – During and Before Covid, under 70s

	During Covid		Before Covid	
Marital Status	Number of responses	**Digital Poverty Index #**	Number of responses	**Digital Poverty Index #**
Widowed	1,026	**6.80**	978	**13.60**
Divorced	3,793	**3.30**	3,995	**6.60**
Married, separated	978	**3.90**	1,206	**5.60**
Married, living together	24,268	**2.00**	24,489	**3.20**
Single, never married	14,939	**2.30**	17,118	**2.90**
Total	45,004	**2.40**	47,786	**3.60**

0 = no digital poverty, i.e. all respondents would have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

On the other hand, for over 70s, digital poverty is lower for married respondents than those who are separated, divorced, single, or widowed (Figure 10b and Table 10b).

Figure 10b. Digital Poverty Index# by Marital Status – During and Before Covid, aged 70+



0 = no digital poverty, i.e. all respondents would have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

Table 10b. Digital Poverty Index# by Marital Status – During and Before Covid, aged 70+

	During Covid		Before Covid	
Marital Status	Number of responses	**Digital Poverty Index #**	Number of responses	**Digital Poverty Index #**
Widowed	2,166	**38.10**	1,772	**48.80**
Divorced	1,139	**23.60**	870	**31.10**
Married, separated	162	**29.60**	122	**34.40**
Married, living together	7,487	**17.50**	5,427	**25.60**
Single, never married	524	**30.00**	381	**44.90**
Total	11,478	**22.70**	8,572	**31.90**

0 = no digital poverty, i.e. all respondents would have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

2. What are the impacts of digital poverty upon productivity and skills?

Digital poverty is significantly associated with less hours worked (stronger association during Covid) (Table 10). Before Covid, people who have not used the Internet for three months worked 10.2% fewer hours than others. During Covid the figure was 27.3%.

Table 10. Actual hours worked in main and second job

	Mean	Percentage difference	n	Standard deviation	F
During Covid					
Used Internet in last 3 months	29.88	27.3	30,703	17.7	63.4
Not used Internet in last 3 months	21.71		302	20.0	
Total	29.80		31,005	17.8	
Before Covid					
Used Internet in last 3 months	32.31	10.2	33,096	16.6	21.2
Not used Internet in last 3 months	29.01		547	18.7	
Total	32.25		33,643	16.6	

Source: LFS

We do not have a direct measure of the association of digital poverty with skills, although people in digital poverty tend to be in lower-paid jobs (see Table 11). There is a highly significant negative correlation of –0.45 between gross weekly pay in main job and not having used the Internet for three months or more. Before Covid, only 0.3% of higher managerial and professional workers have never used the Internet, whereas the figure is 7.1% for those in routine occupations and 17.7% for those unemployed. During Covid the figures are 0.2%, 5.9% and 13.8% respectively.

Table 11. Percentage of respondents who have never used the Internet by job type

	% Who have never used the Internet	
	Before Covid	During Covid
Higher managerial and professional	0.3%	0.2
Lower managerial and professional	0.6%	0.4
Intermediate occupations	1.0%	0.7
Small employers and own account workers	3.7%	3.4
Lower supervisory and technical	3.0%	2.4
Semi-routine occupations	3.7%	3.3
Routine occupations	7.1%	5.9
Never worked and unemployed	17.7%	13.8
Total	6.4%	5.2

3. What communities are most severely affected by digital poverty, and how do impacts vary across and within communities?

Overall, ethnic minorities are only slightly more subject to digital poverty than are the white majority, as reported in Table 1 above. However, for ethnic minorities, disability is much more strongly associated with digital poverty than for the white majority, as reported in Table 9 and illustrated in Figure 9 above.

The main community effect is that more deprived communities suffer more digital poverty. There is a strong correlation between local authority Index of Multiple Deprivation (IOMD) and digital poverty measured by time to having last used the Internet: Pearson correlation R = 0.417 before Covid (n = 315 local authorities) and 0.382 during Covid (n = 310) (both 99% significant by bootstrap), based on all local authorities in England that can be exactly matched between the different datasets (the IOMD does not extend to other UK countries)[21] (see Appendix for itemised table by Local Authorities). This effect leads to a North/ South divide. Specifically, before Covid, the percentage of people who had not used the Internet for three months was 46.7% higher in the rest of the UK compared to the London, Southeast and Southwest regions. During Covid the figure was 50.1%.

Table 12. The North/ South divide

	London, Southeast and Southwest		Other UK regions			% Other regions are greater than London, SE and SW
	Number	%	Number	%	Total	
Before Covid						
Used Internet in last 3 months	16,374	94.03	35,746	91.24	52,120	
Not used Internet in last 3 months	1,040	5.97	3,434	8.76	4,474	46.7
Total	17,414	100	39,180	100	56,594	
During Covid						
Used Internet in last 3 months	17,915	95.13	35,080	92.69	52,995	
Not used Internet in last 3 months	917	4.87	2,768	7.31	3,685	50.1
Total	18,832	100	37,848	100	56,680	

[21] See footnote 3

4. What are the challenges associated with tackling digital poverty in the UK? What are the social, economic and cultural barriers to addressing digital poverty and how can they be effectively and equitably overcome?

The main challenge associated with tackling digital poverty in the UK is that some commonly recommended interventions may be less cost-effective than hoped, *viz*, alleviating financial poverty, providing free equipment and wiring up poor broadband coverage areas. This is because, notwithstanding the correlation between digital poverty and deprivation, this study demonstrates that the most commonly stated reasons by people young enough to be economically active for not having the Internet concern motivation and attitude factors (which are more prevalent in lower-resources groups) rather than directly from income/ cost issues. Issues such as costs and broadband access are mentioned by only few of the individuals in digital poverty. Because for every single person in digital poverty, there are three more who are not in digital poverty, sharing similar age range and facing similar resources challenges, we conclude that barriers to alleviating digital poverty are not mainly, directly economic. We draw attention to the role of lack of literacy in digital poverty for younger people. For older people, issues around complexity represent a significant barrier.

We suggest that these barriers might be overcome by concentrating resources on stimulating motivation through communications (perhaps nudge messages), supporting digital skills, especially for older people, and improving literacy, especially for younger people.

Conclusions

This report presents findings of digital poverty in the UK by analysing data from OFCOM and the Office for National Statistics (ONS). A variety of factors that have an impact on digital poverty are examined. Results confirm the association of digital poverty with deprivation. New findings indicate, first, the role of literacy in digital poverty, especially for young people (aged 16-24); and second, the importance of factors concerning motivation and attitude. A range of factors that affect the association between a variety of factors and digital poverty were also tested (moderators). Impacts of digital poverty upon productivity and skills were identified, as were the severely affected communities. Challenges and barriers for tackling digital poverty are discussed followed by our recommendations to overcome those issues.

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i Tables of counts, cross-tabulations and statistics relating to the variables reported are available from the authors.

ii This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

Appendix. Digital Poverty Index# by Local Authority

With Index of Multiple Deprivation^ and Urban/ Rural*; Ranked by Digital Poverty Before Covid

Rank	*Local Authority*	*Digital Poverty Index during Covid #*	*Number in sample during Covid*	*Index of Multiple Deprivation ^*	*Digital Poverty Index before Covid #*	*Number in sample before Covid*	*Rural (1: darker shade) → Urban (6: lighter shade) **	
1	Sunderland	8.06	183	30.586	14.02	264	6	Major Conurbation
2	South Tyneside	7.41	145	31.509	13.41	151	6	Major Conurbation
3	Great Yarmouth	7.42	64	33.097	12.72	57	3	Urban with Significant Rural
4	Copeland	5.73	48	25.012	11.51	76	1	Predominantly Rural
5	Knowsley	7.5	70	43.006	11.11	72	6	Major Conurbation
6	Forest of Dean	6.5	123	18.013	11.01	84	1	Predominantly Rural
7	Isle of Wight	6.57	137	23.294	10.82	141	1	Predominantly Rural
8	Wolverhampton	7.71	133	32.102	10.32	201	6	Major Conurbation
9	Wyre	8.26	118	20.858	9.91	106	2	Predominantly Rural
10	Fenland	3.3	91	25.426	9.88	86	2	Predominantly Rural
11	Hartlepool	13.06	67	35.037	9.86	71	4	Predominantly Urban
12	East Staffordshire	9.11	96	19.028	9.56	102	3	Urban with Significant Rural
13	Middlesbrough	6.43	105	40.46	9.55	110	4	Predominantly Urban
14	Barrow-in-Furness	9.62	39	31.117	9.55	55	3	Urban with Significant Rural
15	Chesterfield	5.83	120	24.926	9.54	97	4	Predominantly Urban
16	Derby	1.7	191	26.323	9.43	212	4	Predominantly Urban
17	Havering	4.4	216	16.789	9.32	161	6	Major Conurbation
18	Stratford-on-Avon	2.28	186	11.728	9.11	107	1	Predominantly Rural
19	Mansfield	9.41	85	28.503	8.97	92	4	Predominantly Urban
20	Liverpool	6.48	293	42.412	8.96	307	6	Major Conurbation
21	Dover	5.03	144	22.161	8.93	112	3	Urban with Significant Rural
22	County Durham	6.6	477	26.793	8.74	509	2	Predominantly Rural
23	Bromsgrove	3.96	101	11.697	8.53	85	4	Predominantly Urban
24	Lichfield	6.13	106	12.566	8.5	103	3	Urban with Significant Rural
25	Adur	7.02	57	17.594	8.33	60	4	Predominantly Urban
26	Basildon	4.04	130	23.243	8.33	120	4	Predominantly Urban
27	West Devon	2.4	52	18.052	8.33	63	1	Predominantly Rural
28	Stoke-on-Trent	5.75	187	34.504	8.28	166	4	Predominantly Urban
29	East Lindsey	9.21	152	29.892	8.2	122	1	Predominantly Rural
30	Plymouth	6.03	195	26.619	8.13	209	4	Predominantly Urban
31	Rotherham	5.17	203	29.55	8.1	210	5	Minor Conurbation
32	Staffordshire Moorlands	5.29	85	15.04	8.06	93	2	Predominantly Rural
33	Kettering	1.72	116	19.23	8.06	93	4	Predominantly Urban
34	Leicester	4.51	183	30.877	8.04	202	4	Predominantly Urban
35	Amber Valley	4.39	114	17.97	8.03	109	5	Minor Conurbation
36	Hertsmere	4.41	85	13.938	7.98	47	6	Major Conurbation

37	Coventry	4.94	258	25.613	7.97	276	4	Predominantly Urban
38	Nuneaton and Bedworth	3.8	92	23.54	7.85	86	4	Predominantly Urban
39	Hounslow	2.54	138	21.487	7.79	122	6	Major Conurbation
40	Kingston upon Hull, City of	8.29	193	40.564	7.76	190	4	Predominantly Urban
41	West Lindsey	4.03	124	20.355	7.76	87	1	Predominantly Rural
42	Hinckley and Bosworth	2.6	96	13.461	7.76	87	2	Predominantly Rural
43	Stockton-on-Tees	5.72	188	25.79	7.65	170	4	Predominantly Urban
44	Wakefield	4.23	272	27.306	7.61	345	4	Predominantly Urban
45	South Holland	1.7	88	17.896	7.61	92	2	Predominantly Rural
46	St. Helens	4.25	153	31.518	7.48	137	6	Major Conurbation
47	Sandwell	7.34	109	34.884	7.42	256	6	Major Conurbation
48	Bradford	5.04	367	34.666	7.35	408	6	Major Conurbation
49	Gosport	1.33	94	20.541	7.26	62	4	Predominantly Urban
50	North Lincolnshire	6.36	118	22.096	7.19	146	3	Urban with Significant Rural
51	Shropshire	3	308	17.153	7.19	372	2	Predominantly Rural
52	Castle Point	6.76	74	16.842	7.14	70	4	Predominantly Urban
53	Torbay	7.5	140	28.104	7.14	133	4	Predominantly Urban
54	Tameside	6.51	146	31.374	7.12	172	6	Major Conurbation
55	North Devon	3.41	132	20.559	7.09	67	2	Predominantly Rural
56	Tonbridge and Malling	2.75	109	13.333	7.03	96	3	Urban with Significant Rural
57	Gedling	3.3	144	14.894	6.98	86	5	Minor Conurbation
58	Blaby	1.12	112	10.629	6.94	72	4	Predominantly Urban
59	Chiltern			6.952	6.94	72	3	Urban with Significant Rural
60	Tower Hamlets	1.76	85	27.913	6.91	152	6	Major Conurbation
61	King's Lynn and West Norfolk	2.59	135	23.72	6.88	160	2	Predominantly Rural
62	South Kesteven	6.02	133	13.499	6.85	124	2	Predominantly Rural
63	Enfield	3.8	171	25.781	6.84	234	6	Major Conurbation
64	Warwick	4.77	173	12.005	6.8	147	4	Predominantly Urban
65	Blackpool	6.12	94	45.039	6.78	107	4	Predominantly Urban
66	Westminster	7.01	82	20.339	6.69	71	6	Major Conurbation
67	Kingston upon Thames	3.06	139	11.381	6.68	116	6	Major Conurbation
68	North West Leicestershire	2.6	96	14.573	6.67	90	2	Predominantly Rural
69	Redcar and Cleveland	4.43	96	29.792	6.67	105	3	Urban with Significant Rural
70	Broxbourne	6.48	81	17.989	6.64	64	6	Major Conurbation
71	Halton	6.2	121	32.325	6.62	68	4	Predominantly Urban
72	Thanet	4.29	140	31.314	6.62	102	4	Predominantly Urban
73	Northumberland	4.03	366	22.079	6.61	363	2	Predominantly Rural
74	Kirklees	5.33	380	25.151	6.54	386	6	Major Conurbation
75	Wandsworth	1.11	180	16.611	6.54	172	6	Major Conurbation
76	South Staffordshire	3.68	95	13.124	6.51	73	3	Urban with Significant Rural
77	Shepway	4.84	93	24.149	6.5	100		

78	Stevenage	4.76	84	19.695	6.49	77	4	Predominantly Urban
79	Blackburn with Darwen	5.24	62	36.013	6.49	104	4	Predominantly Urban
80	Lancaster	6.57	99	24.165	6.48	162	3	Urban with Significant Rural
81	Calderdale	4.91	168	26.351	6.42	183	6	Major Conurbation
82	East Riding of Yorkshire	5.69	382	15.605	6.38	325	2	Predominantly Rural
83	Broxtowe	3.57	105	14.238	6.35	126	5	Minor Conurbation
84	Bolton	5.49	173	30.691	6.33	245	6	Major Conurbation
85	Telford and Wrekin	3.3	144	24.988	6.32	186	4	Predominantly Urban
86	West Suffolk	4.59	169	16.245	6.25	96		
87	Ribble Valley	1.07	70	10.594	6.25	52	1	Predominantly Rural
88	Eden	7.33	58	16.328	6.25	56	1	Predominantly Rural
89	Mid Devon	4.72	90	16.928	6.25	88	1	Predominantly Rural
90	Broadland	3.94	127	11.817	6.19	109	3	Urban with Significant Rural
91	Rochford	2.97	118	10.449	6.15	65	4	Predominantly Urban
92	Islington	2.97	118	27.535	6.11	135	6	Major Conurbation
93	Wigan	7.93	227	25.713	6.1	246	6	Major Conurbation
94	Scarborough	8.49	109	26.28	6.1	123	3	Urban with Significant Rural
95	Malvern Hills	2.02	99	16.066	6.08	74	2	Predominantly Rural
96	Newark and Sherwood	3.71	101	19.227	6.05	124	2	Predominantly Rural
97	Wyre Forest	6.63	98	22.437	6.04	91	3	Urban with Significant Rural
98	Bassetlaw	6.4	121	22.588	6.01	129	2	Predominantly Rural
99	Melton	8.33	51	12.532	5.97	67	1	Predominantly Rural
100	Cheshire West and Chester	3.94	336	18.083	5.96	281	3	Urban with Significant Rural
101	Tendring	8.13	126	30.484	5.95	147	2	Predominantly Rural
102	Barnsley	8.33	213	29.933	5.94	181	5	Minor Conurbation
103	Oadby and Wigston	6.82	44	12.958	5.92	38	4	Predominantly Urban
104	Surrey Heath	0	55	8.066	5.88	68	4	Predominantly Urban
105	Gateshead	3.09	186	28.217	5.79	151	6	Major Conurbation
106	North East Derbyshire	3.98	113	17.399	5.73	96	4	Predominantly Urban
107	Ashfield	3.16	79	26.308	5.73	144	4	Predominantly Urban
108	Walsall	6.87	182	31.555	5.7	193	6	Major Conurbation
109	Dudley	6.35	185	24.103	5.66	256	6	Major Conurbation
110	Epping Forest	2.88	104	15.068	5.65	84	3	Urban with Significant Rural
111	Braintree	6.25	104	14.723	5.65	124	2	Predominantly Rural
112	Newham	4.72	90	29.577	5.64	173	6	Major Conurbation
113	Warrington	5.09	172	18.942	5.63	160	4	Predominantly Urban
114	Selby	5.38	93	12.73	5.61	107	1	Predominantly Rural
115	Mid Suffolk	2.64	104	13.225	5.59	94	1	Predominantly Rural
116	Sheffield	3.86	473	27.06	5.58	466	5	Minor Conurbation
117	Bolsover	14.15	53	25.047	5.56	72	3	Urban with Significant Rural
118	Charnwood	6.36	169	13.238	5.54	149	4	Predominantly Urban
119	Haringey	0.52	143	27.956	5.53	113	6	Major Conurbation

120	Mendip	6.1	123	16.6	5.51	118	1	Predominantly Rural
121	Harrogate	3.4	206	10.897	5.45	165	3	Urban with Significant Rural
122	Oldham	7.01	157	33.155	5.43	175	6	Major Conurbation
123	Croydon	2.41	249	22.477	5.41	245	6	Major Conurbation
124	Carlisle	3.79	112	21.997	5.41	111	3	Urban with Significant Rural
125	East Northamptonshire	4.31	87	13.897	5.38	65	2	Predominantly Rural
126	Waltham Forest	2.33	150	25.209	5.37	135	6	Major Conurbation
127	Torridge	4.58	60	23.269	5.36	56	1	Predominantly Rural
128	Stafford	3.23	155	13.678	5.34	131	3	Urban with Significant Rural
129	Erewash	8.91	101	18.818	5.34	117	5	Minor Conurbation
130	Birmingham	6.3	607	38.067	5.3	839	6	Major Conurbation
131	South Norfolk	4.59	147	13.318	5.27	128	1	Predominantly Rural
132	Manchester	2.38	231	40.005	5.25	395	6	Major Conurbation
133	Havant	4.02	112	21.806	5.22	115	4	Predominantly Urban
134	Wychavon	4.09	159	15.766	5.21	120	1	Predominantly Rural
135	North East Lincolnshire	4.85	98	31.335	5.2	125	4	Predominantly Urban
136	Cherwell	2.33	150	14.41	5.15	131	3	Urban with Significant Rural
137	East Hampshire	2.34	128	10.284	5.13	112	1	Predominantly Rural
138	Burnley	6.03	58	37.793	5.13	78	4	Predominantly Urban
139	Camden	2.94	68	20.131	5.12	122	6	Major Conurbation
140	Breckland	2.61	153	19.614	5.09	113	1	Predominantly Rural
141	Maidstone	4.79	120	16.503	5.08	128	3	Urban with Significant Rural
142	Tamworth	1.25	60	21.061	5.06	89	4	Predominantly Urban
143	Exeter	1.74	115	16.215	5.05	99	4	Predominantly Urban
144	Canterbury	2.78	162	16.798	5.03	144	4	Predominantly Urban
145	East Devon	5.07	202	12.764	5.03	164	2	Predominantly Rural
146	Northampton	7.48	204	23.358	5.03	174	4	Predominantly Urban
147	Medway	5.5	159	23.936	5.03	174	4	Predominantly Urban
148	Doncaster	8.78	222	30.289	5.02	224	5	Minor Conurbation
149	Daventry	2.47	81	13.184	5	75	1	Predominantly Rural
150	Stockport	4.84	274	20.826	4.98	236	6	Major Conurbation
151	Cornwall	5.17	585	23.072	4.97	463	1	Predominantly Rural
152	Stroud	2.07	145	10.797	4.92	132	3	Urban with Significant Rural
153	New Forest	3.98	220	13.015	4.89	174	3	Urban with Significant Rural
154	Salford	5.62	129	34.21	4.88	205	6	Major Conurbation
155	Welwyn Hatfield	3.23	93	14.215	4.88	82	4	Predominantly Urban
156	Eastleigh	2.58	126	10.192	4.87	113	4	Predominantly Urban
157	Dartford	7.21	52	18.812	4.85	67	6	Major Conurbation
158	Wycombe			10.742	4.82	166	3	Urban with Significant Rural
159	Luton	6.86	102	25.908	4.79	141	4	Predominantly Urban
160	Dorset			15.735	4.75	336		
161	South Northamptonshire	4.02	112	7.652	4.72	90	1	Predominantly Rural

162	North Norfolk	2.42	124	21.058	4.69	80	1	Predominantly Rural
163	Hambleton	0.67	112	11.987	4.69	96	1	Predominantly Rural
164	Brent	2.87	157	25.558	4.65	129	6	Major Conurbation
165	Peterborough	5.7	158	27.821	4.64	183	4	Predominantly Urban
166	Newcastle upon Tyne	5.1	245	29.79	4.62	222	6	Major Conurbation
167	Ashford	2.84	132	18.546	4.59	98	3	Urban with Significant Rural
168	Swale	0.2	122	27.076	4.58	131	2	Predominantly Rural
169	Lambeth	2.47	162	25.422	4.58	202	6	Major Conurbation
170	Redditch	8.05	59	22.524	4.57	82	4	Predominantly Urban
171	Newcastle-under-Lyme	4.57	104	18.929	4.55	99	4	Predominantly Urban
172	Teignbridge	3.2	172	15.893	4.53	127	2	Predominantly Rural
173	Brighton and Hove	1.97	228	20.761	4.52	166	4	Predominantly Urban
174	Herefordshire, County of	5.89	208	18.89	4.46	196	2	Predominantly Rural
175	Wirral	4.33	254	29.589	4.45	281	6	Major Conurbation
176	York	2.36	222	11.727	4.43	203	4	Predominantly Urban
177	Kensington and Chelsea	5.63	40	21.526	4.41	51	6	Major Conurbation
178	Watford	1.45	86	15.41	4.41	51	6	Major Conurbation
179	Hastings	3.4	81	34.281	4.39	57	4	Predominantly Urban
180	West Lancashire	4.48	106	18.645	4.38	80	3	Urban with Significant Rural
181	Hillingdon	4.58	131	18.223	4.37	183	6	Major Conurbation
182	Spelthorne	7.73	97	14.943	4.35	92	6	Major Conurbation
183	Greenwich	1.71	146	24.464	4.34	167	6	Major Conurbation
184	Wiltshire	3.87	555	13.447	4.32	457	2	Predominantly Rural
185	Nottingham	3.11	193	34.891	4.31	226	5	Minor Conurbation
186	Central Bedfordshire	4.64	237	12.152	4.3	285	2	Predominantly Rural
187	Dacorum	2.25	122	13.004	4.29	105	3	Urban with Significant Rural
188	Darlington	6.94	108	25.657	4.27	123	4	Predominantly Urban
189	Southend-on-Sea	0.6	168	22.375	4.26	141	4	Predominantly Urban
190	Somerset West and Taunton	2.63	133	19.142	4.25	163		
191	Woking	0	92	10.804	4.22	77	6	Major Conurbation
192	Pendle	2.08	48	30.723	4.21	89	4	Predominantly Urban
193	Cannock Chase	9.93	68	20.426	4.17	72	3	Urban with Significant Rural
194	Allerdale	1.01	74	22.938	4.17	102	1	Predominantly Rural
195	Cheshire East	4.11	414	14.475	4.14	338	3	Urban with Significant Rural
196	Sefton	4.13	260	27.035	4.13	236	6	Major Conurbation
197	Test Valley	1.71	161	11.931	4.13	115	3	Urban with Significant Rural
198	Swindon	4.8	203	18.622	4.09	171	4	Predominantly Urban
199	North Tyneside	5.61	223	22.279	4.09	165	6	Major Conurbation
200	Ryedale	8.09	68	15.665	4.09	55	1	Predominantly Rural
201	Slough	2.24	67	22.965	4.08	92	4	Predominantly Urban
202	East Cambridgeshire	9.3	86	11.507	3.9	77	1	Predominantly Rural
203	East Suffolk	6.45	244	19.56	3.87	142		

204	Mid Sussex	3.44	138	7.747	3.86	110	4	Predominantly Urban
205	Trafford	3.59	216	16.088	3.85	208	6	Major Conurbation
206	Brentwood	4.55	66	10.007	3.85	52	3	Urban with Significant Rural
207	Southampton	3.4	184	26.876	3.83	196	4	Predominantly Urban
208	South Somerset	3.51	185	17.347	3.82	144	2	Predominantly Rural
209	Babergh	3.54	120	14.267	3.81	105	1	Predominantly Rural
210	Bedford	3.15	151	18.932	3.8	158	3	Urban with Significant Rural
211	Bath and North East Somerset	2.96	186	11.745	3.79	178	3	Urban with Significant Rural
212	Leeds	3.84	684	27.301	3.75	726	6	Major Conurbation
213	South Bucks	-25		9.481	3.75	60	3	Urban with Significant Rural
214	Rushmoor	1.09	69	15.903	3.75	80	4	Predominantly Urban
215	Ipswich	5.83	90	25.89	3.72	121	4	Predominantly Urban
216	Rossendale	1.27	59	24.062	3.72	74	4	Predominantly Urban
217	Cheltenham	1.36	129	14.26	3.71	101	4	Predominantly Urban
218	Huntingdonshire	6.13	159	12.55	3.7	169	1	Predominantly Rural
219	Eastbourne	3.27	84	22.11	3.69	61	4	Predominantly Urban
220	North Somerset	2.51	219	15.825	3.67	211	3	Urban with Significant Rural
221	Gloucester	5.3	99	21.807	3.63	124	4	Predominantly Urban
222	Sedgemoor	3.06	147	21.306	3.6	139	2	Predominantly Rural
223	Hackney	0.55	91	32.526	3.59	160	6	Major Conurbation
224	North Kesteven	3.41	110	11.553	3.57	91	1	Predominantly Rural
225	South Lakeland	4.03	118	12.501	3.57	119	1	Predominantly Rural
226	Corby	3.81	59	25.706	3.57	56	4	Predominantly Urban
227	Portsmouth	6.61	140	26.899	3.54	134	4	Predominantly Urban
228	South Derbyshire	6.06	99	14.494	3.53	92	3	Urban with Significant Rural
229	Bromley	4.08	245	14.163	3.53	269	6	Major Conurbation
230	Bristol, City of	4.62	352	26.363	3.53	432	4	Predominantly Urban
231	Redbridge	3.55	148	17.203	3.53	170	6	Major Conurbation
232	Milton Keynes	1.8	264	17.98	3.51	228	4	Predominantly Urban
233	South Oxfordshire	3.48	158	8.459	3.51	164	1	Predominantly Rural
234	Harrow	3.89	148	15.031	3.5	157	6	Major Conurbation
235	Lewisham	3.62	207	26.661	3.5	193	6	Major Conurbation
236	South Cambridgeshire	2.49	181	8.496	3.48	158	2	Predominantly Rural
237	East Hertfordshire	3.48	122	8.188	3.47	144	3	Urban with Significant Rural
238	Winchester	2.24	123	9.615	3.46	130	2	Predominantly Rural
239	Wealden	4.45	219	12.311	3.44	109	1	Predominantly Rural
240	Chelmsford	2.36	180	12.221	3.42	146	4	Predominantly Urban
241	High Peak	1.58	79	15.642	3.42	73	2	Predominantly Rural
242	Sevenoaks	1.36	110	12.437	3.39	59	2	Predominantly Rural
243	Derbyshire Dales	2.25	89	11.895	3.38	74	1	Predominantly Rural
244	Vale of White Horse	1.71	161	8.358	3.37	126	2	Predominantly Rural
245	Uttlesford	3.09	97	9.258	3.36	67	1	Predominantly Rural

246	Wellingborough	2.44	82	21.676	3.33	75	3	Urban with Significant Rural
247	Lincoln	5.69	101	26.889	3.26	92	4	Predominantly Urban
248	Tewkesbury	2.21	102	12.142	3.24	85	2	Predominantly Rural
249	Cambridge	0.71	106	14.855	3.23	124	4	Predominantly Urban
250	Hammersmith and Fulham	3.57	70	22.27	3.23	62	6	Major Conurbation
251	Bury	3.3	144	23.682	3.2	164	6	Major Conurbation
252	Reading	5.49	123	19.619	3.07	122	4	Predominantly Urban
253	Richmondshire	5.29	52	12.135	3.06	49	1	Predominantly Rural
254	Colchester	3.67	184	16.778	3.06	188	3	Urban with Significant Rural
255	Solihull	6.92	206	17.37	3.05	172	6	Major Conurbation
256	Chorley	5.12	127	16.863	2.98	84	3	Urban with Significant Rural
257	Horsham	3.6	111	9.89	2.98	126	2	Predominantly Rural
258	Waverley	1.35	148	7.494	2.97	101	2	Predominantly Rural
259	Southwark	1.51	166	25.811	2.93	230	6	Major Conurbation
260	Elmbridge	1.07	140	7.944	2.83	106	6	Major Conurbation
261	St Albans	0.85	176	8.339	2.83	106	4	Predominantly Urban
262	Hyndburn	2.83	53	34.333	2.82	71	4	Predominantly Urban
263	Ealing	4.35	155	22.71	2.8	125	6	Major Conurbation
264	Three Rivers	2.14	70	9.871	2.73	55	6	Major Conurbation
265	Bracknell Forest	1.28	117	10.241	2.63	114	4	Predominantly Urban
266	Epsom and Ewell	1.76	85	8.833	2.63	57	6	Major Conurbation
267	Arun	3.18	165	18.638	2.54	118	4	Predominantly Urban
268	Crawley	3.32	98	18.94	2.47	91	4	Predominantly Urban
269	Fylde	4.65	86	15.875	2.47	81	4	Predominantly Urban
270	North Hertfordshire	3.6	146	11.627	2.44	133	3	Urban with Significant Rural
271	Richmond upon Thames	3.21	179	9.425	2.44	154	6	Major Conurbation
272	Rugby	2.33	118	14.119	2.41	83	4	Predominantly Urban
273	Barnet	2.77	253	16.148	2.37	253	6	Major Conurbation
274	Rushcliffe	3.89	148	7.18	2.37	116	2	Predominantly Rural
275	Rochdale	6.68	161	34.415	2.31	184	6	Major Conurbation
276	South Ribble	7.24	107	15.33	2.27	99	4	Predominantly Urban
277	Cotswold	5.31	113	11.061	2.22	90	1	Predominantly Rural
278	Preston	1.49	101	29.531	2.21	68	4	Predominantly Urban
279	West Oxfordshire	2.58	126	8.684	2.17	92	1	Predominantly Rural
280	Windsor and Maidenhead	3.53	156	8.376	2.16	174	4	Predominantly Urban
281	Worcester	4.35	92	20.414	2.14	117	4	Predominantly Urban
282	South Gloucestershire	1.69	251	11.66	2.11	213	4	Predominantly Urban
283	Harborough	1.49	101	8.015	2.11	95	1	Predominantly Rural
284	Reigate and Banstead	2.89	121	11.276	2.08	108	4	Predominantly Urban
285	Rutland	0	61	8.381	2.08	36	1	Predominantly Rural
286	Basingstoke and Deane	2.72	184	12.823	2.07	145	3	Urban with Significant Rural

287	Lewes	3.93	89	15.758	1.97	89	3	Urban with Significant Rural
288	Maldon	7.5	60	14.169	1.89	66	1	Predominantly Rural
289	North Warwickshire	5.68	66	17.907	1.87	67	1	Predominantly Rural
290	Boston	4.27	41	22.967	1.83	41	3	Urban with Significant Rural
291	Harlow	4.93	76	21.413	1.81	69	4	Predominantly Urban
292	Sutton	1.48	118	13.987	1.79	154	6	Major Conurbation
293	Chichester	4.05	105	14.085	1.68	119	2	Predominantly Rural
294	Worthing	2.89	121	17.012	1.6	94	4	Predominantly Urban
295	Rother	7.37	112	19.768	1.56	64	2	Predominantly Rural
296	Norwich	0.84	89	27.599	1.54	130	4	Predominantly Urban
297	Thurrock	5.42	120	20.928	1.46	120	6	Major Conurbation
298	Fareham	3.62	152	9.019	1.37	128	4	Predominantly Urban
299	Guildford	2.69	130	9.395	1.36	110	4	Predominantly Urban
300	Oxford	1.67	120	16.707	1.28	117	4	Predominantly Urban
301	Craven	4.17	72	12.76	1.22	41	1	Predominantly Rural
302	Barking and Dagenham	1.21	62	32.768	1.17	107	6	Major Conurbation
303	West Berkshire	4.71	170	9.952	1.15	131	3	Urban with Significant Rural
304	Mole Valley	4.17	102	9.511	1.09	69	3	Urban with Significant Rural
305	Wokingham	1.79	154	5.846	0.96	183	4	Predominantly Urban
306	Runnymede	0.4	63	12.012	0.81	62	6	Major Conurbation
307	Aylesbury Vale			11.183	0.79	159	2	Predominantly Rural
308	South Hams	2.83	115	13.724	0.7	71	1	Predominantly Rural
309	Bexley	2.62	143	16.273	0.68	147	6	Major Conurbation
310	Merton	1.3	154	14.649	0.52	143	6	Major Conurbation
311	Hart	2.8	134	5.544	0.52	97	3	Urban with Significant Rural
312	Gravesham	4.92	61	21.414	0.49	51	6	Major Conurbation
313	Tunbridge Wells	3.68	102	11.31	0	87	3	Urban with Significant Rural
314	Tandridge	1.5	50	11.896	0	56	3	Urban with Significant Rural
315	City of London	0	11	14.72	0	10	6	Major Conurbation
	Total responses		44515			**44240**		

Notes:

0 = no digital poverty, i.e. all respondents have used the Internet within the previous three months; 100 would mean no respondents had used the Internet within the previous three months.

^ Index of Multiple Deprivation (IOMD 2019) from the Ministry of Housing, Communities and Local Government.

* Rural Urban Classification (2011) of Local Authority Districts in England (ONS):

1 = Mainly (80% +) rural including hub towns;
2 = Largely (50-79%) rural including hub towns;
3 = Urban with significant rural (26-49%) including hub towns;
4 = Urban with city and town;
5 = Urban with minor conurbation;
6 = Urban with major conurbation.

Note: A small number of local authority areas are omitted as cannot be matched with the Index of Multiple Deprivation due to boundary changes. Blank cells indicate instances of missing or outdated local authority data.