Digital media use: differences and inequalities in relation to class and age

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Simeon J. Yates, John Kirby, Eleanor Lockley and Stephen Crone

Introduction

The study of differences in access to and use of Information and Communication Technologies (ICTs) has been undertaken since the 1960's. Such work has often taken a strongly empirical approach. It has documented inequities in access, rates of use and impacts on such things as education, work and lifestyle. Such work has repeatedly identified inequalities in access for nearly all forms of ICT – for example in regard to the telephone (see Fischer, 1992), computers (see Bolt and Crawford, 2000) and more recently the Internet. This paper follows on in that tradition but shifts the focus onto variations in use for those *with* access to the Internet in the UK. The data were collected and the majority of analyses competed before the recent Dutch study (Van Deursen and Van Dijk, 2014) that similarly documents socio-economic variations in usage patterns in the Netherlands. The analysis presented here uses UK data and complements this work.

A cursory review of contemporary media coverage would lead to the impression that digital media have become pervasive and ubiquitous in UK society. Yet, as our analyses will show, two fifths (41%) of the UK population have no access, limited access or are limited users of digital media. Our own qualitative action research has found evidence of considerable 'churn' in access to ICTs for those on lower incomes and evidence of structural market barriers to access for these citizens (Yates, Kirby and Lockley, 2014, 2015). Yet we live in a context where assumptions about the pervasiveness of digital media now influence and shape educational, social, economic and welfare policies in many developed nations. This interplay between new social policies and the material realties of digital access has been a focus of our recent research work in collaboration with UK city governments, national charities and local groups.

In this paper we take a national perspective and draw upon the OfCom Media Literacy 2013 survey to explore how digital media use varies in regard to two major social variables – class and age. Both class and age feature predominantly in UK policy on digital access and use. Class and age are invoked as either things that create barriers to access or as issues to be addressed and managed through digital media. The paper presents a factor analysis of the OfCom data that identifies five main areas of digital media use. These five factors are then subjected to a multiple analysis of variance to explore the effects across, between and within age and class categories. A cluster analysis based on the factors identifies seven main 'User Types' that are again compared across class and age. In conclusion the paper notes that age still acts as the major explanatory variable for overall use and some specific types of use, but that class also independently acts to explain patterns of digital media use.

Policy context

Our own work developed out of projects focused on supporting digital inclusion through regional government policies (Goraya, Light and Yates, 2012; Yates, Kirby and Lockley, 2014). This work primarily started from the assumption that digital inclusion brought a variety of social, economic and educational benefits. Supporting inclusion policies would therefore help bring these benefits to more marginalised communities. Regional policies reflect a wider national and international policy context. The number and extent of these policy interventions are testimony to the importance placed by political and economic actors on ensuring large-scale access to ICT[i].

In the UK the focus changed from 2010 onwards as government policy shifted, especially under regimes of 'austerity', to one of service delivery through 'digital by default. This is first noted in the 2011 UK Government ICT Strategy and developed in 2013 Digital Strategy. This includes all forms of service from tax returns, to hospital appointments, to social welfare. It is the impact upon services for those in marginalised communities that has been our focus. As prior work (White & Selwyn, 2013; Helsper, 2011) has noted, and as our analysis below will expand, in the UK the majority of welfare service users are members of those communities most likely to be digitally excluded. Yet, despite this, current UK government welfare policies are based upon a 'digital-by-default' approach to service delivery, wherein face-to-face, telephone and paper-based interactions are replaced by the use of web-based services or mobile 'apps'. In considering the roots of the 'digital-by-default' policy, it is important to remember that technology-based policies are as much imbued with political and ideological goals as policies in any other area (Grint K, Woolgar S, 1997).

So, although initial rhetoric surrounding 'digital-by-default' appealed to the need to bring government services 'up to date' (that is, to match banks, insurers and holiday firms in their use of digital media), a more consistent explanation for its adoption lies in anticipated 'efficiency savings'. The government's Digital Strategy (Cabinet Office, 2013) claims "that moving services from offline to digital channels will save between £1.7 and £1.8 billion a year". It is important to remember that digital-by-default is not about back-office services, as these have been computerised for decades. Digital-by-default in contrast, focuses on the clients' interaction with government. The web sites and apps to deliver this are predominantly developed and supported by the private sector.

In other work we have debated the manner in which costs are saved and how these may in fact be simply 'shifted' elsewhere in the social welfare system to charities and other service providers (Yates, Kirby and Lockley, 2015). As a result access to basic government services such as income support, social housing, educational and health provision may be strongly affected by access to digital media and levels of digital media literacy. In this context a more detailed understanding of how different social groups access and use these media is needed. As we will demonstrate social class is one of the most reliable predictors of access and use.

However, age remains the most significant predictor of access and use. This has led some think tanks to claim that issues of access are 'temporary'. It is crudely argued that, as the population ages and older non-users pass away, a greater proportion of citizens will be online (see Policy Exchange, 2013). We would note three important flaws in the simple model of a reduction in inequalities as age demographics change over time. First, many of the older citizens who currently find themselves excluded are former IT users who had access at earlier points in their lives. Second, the issue is not just about access but inequalities in types and levels of use. Third, variations in use with age will reflect aspects of life style, life stage and inequalities that vary with age – not just experience with ICTs.

Academic context

As we noted above many authors have explored the question of the 'digital divide' – of inequalities in access to ICT. It has been explored on a global scale (Hargittai, 1999; Warschauer, 2003; The Economist, 2013; Bauerlein, eds., 2011), within nations (LaRose, et. al., 2007; National Telecommunications and Information Administration, 2001) and between communities (Green et. al., 2007; Livingstone and Helsper, 2007; Winchester, 2009). Where there is a clear gulf between those with and without access, overt talk of a 'divide' is meaningful. This is still the case for global ICT access and holds for many developing nations where large numbers of citizens still have limited access to ICT. Yet in a number of developed nations access to some form of ICT is perceived to be close to ubiquitous – be it a computer, mobile phone, smart TV or tablet and whether at home, work, in education or social life. Though in fact notable differences in levels of access remain. Debates over access to ICT have also shifted as technology changed from general telecommunications, to home computing, to Internet access and now to smart mobile media. Of late access to the Internet via an appropriate device has come to act as the primary indicator of being connected to the digital realm – the basic necessity for the digital citizen.

We have identified over five hundred separate English language academic and policy publications since 2000 that report research relevant to issues of Internet or digital media access or inequality. This set of papers does not include the very large body of work on computer-mediated-communication, mobile and interpersonal digital media use or on issues of child and citizen safety online. The set does include academic papers, government reports (mainly UK, US and EU), consultant reports, and reports from charitable organisations. The majority of these publications report on empirical studies of digital media use. They focus on issues of access, specific contexts of use such as education (e.g. Wei and Hindman, 2011) or commerce (e.g. Liebermann and Iyer, 2004; Jackson, et. al., 2001), citizenship (e.g. Bimber, 1999), health and disability (e.g. Hale, 2010), and regional, national and urban variations (e.g. Akca, Sayili, and Esengun, 2007).

A consistent trope in this work starts with assertions of the value of being on-line, identifies a digitally or more broadly marginalised group and then empirically or through cases studies documents the facts of, implications of, or the potential digital solutions to, these inequalities. Collected together this work presents a wide and varied evidence base for the forms and functions of differences and inequalities in digital media use. A systematic review of this literature is provided in Yates, Kirby and Lockley (in press). Much of the empirical work that we have explored is either strongly based in psychological models of technology acceptance/engagement or sociologically 'atheoretical' when reporting on empirical observations of digital inequalities. Where a clear theoretical approach is identified the major foci are:

- Psychological theories of attitude, use and skills (e.g. Eastin, and LaRose, 2000)
- Diffusion of innovations and technology acceptance – (e.g. Wareham, Levy, and Shi, 2004)

- Knowledge or information gap hypothesis – (e.g. Bonfadelli, 2002)
- Social psychological theories (e.g. Partridge, 2012; Helsper and Reisdorf, 2013)
- Uses and gratifications (e.g. Song et. al., 2004)
- Social theories of structure and action: Weber (Graham, 2010); Structuration Theory (Mason and Hacker, 2003); Communicative and Strategic Action (Fuchs, 2009)

Networked society theories are extensively discussed (especially Castells, 1996, 1997, 1998; and van Dijk, 1999, 2005) but these often provide a contextual backdrop to studies and not the focal point for theoretical application. More generally papers apply theories that seek to explain individual motivations, skills and attitudes as explanations for use and uptake (or lack thereof) – such as models of technology acceptance and uses and gratifications. This individual and motivational focus often reflects the underlying policy or moral aims of the work to address the social consequences of digital exclusion and inequality. Very often these consequences are identified through theories of "knowledge and information gaps" whereby digital access exacerbates social inequalities through inequities in access to information.

We have great sympathy with the majority this work and we too see the benefits of personal, local and contextual understandings – especially as it can support more thoughtful hyper-local interventions (Goraya, Light and Yates, 2012; Yates, Kirby, and Lockley, 2014). We also would argue that a consequence of, and reinforcing aspect of, digital inequalities are growing 'types', not just levels of information and knowledge gaps. Having said this we believe that the bulk of the literature to date has not developed a robust understanding of patterns of digital inequality as reflecting and potentially reinforcing the longstanding very material social inequalities that exist in contemporary societies. In other words the focus on individual motivations to access ICTs – rightly driven by policy needs to engage citizens with digital media – can lead to a more limited sociological understanding of the digital inequalities of access and use.

The focus on individual motivation informs much of the strategic thinking behind "digital inclusion" campaigns and interventions by government and voluntary organisations. Our experience suggests that while this theoretical framework might appear to fit well when those digitally excluded are elderly, it fails to address key issues facing younger people. For example, we found that the overwhelming majority of people visiting a local government office to complete online applications for social housing were under 65. Most of these younger people had the necessary skills to complete their online applications without assistance from staff. It could also be argued that they had a strong individual motivation. However, for most of these younger people the main reason for visiting the office to complete their online applications was because they did not have access to the Internet elsewhere. This experience suggests that, for digitally excluded younger people, individual motivation and skills might be less important factors than being able to afford home or consistent access. Being able to afford home Internet access is likely to correspond closely with household socio-economic class. This might further suggest different explanations of digital exclusion of the elderly compared with those younger people on lower incomes.

Of course too broad brush a sociological or economic view risks ignoring the specifics of citizens lifeworlds that may be key to policy interventions. A middle level may be found in areas such as cultural studies where differences in media use may reflect differences in cultural practice and value (Hoggart, 1957) and which in turn reflect broader issues of social and cultural capital (Bourdieu, 1986, 1991). This focus on social and cultural capital and digital exclusion can be found in the work of Helsper (2012) and Ragnedda and Muschert (2013).

Focus of the current analysis

Taking our lead from these approaches and our fieldwork experience we sought to examine how the two policy and theoretical variables of age and class play out in a UK national survey of digital medial access and use. First, we sought to examine whether or not age was the sole determining factor in digital inequalities. If not then this undermines the concomitant conclusion that it would disappear "naturally" over time – an outcome predicted by arguments in both policy documents and think tank arguments. Second, we sought to understand if age and class acted independently or in combination. This would lead to important interactions. If the variables acted as multipliers we might see youth mitigating class inequalities or class exacerbating age inequalities. Third, we sought to develop measures of access, levels of use, types of use and different types of user. This would provide evidence of potential usage types linked to life stage, class, age and in future analyses other demographic variables such as health and other types of media use (see Yates, S.J., Kirby, J. and Lockley, E. (in press)). The goal of this paper is therefore to provide the empirical evidence for taking stock and looking to develop a more robust sociological model of digital inequality that takes into onto account broader considerations of social inequality.

OfCom survey, data and dimension reduction

OFCOM Data Set

The empirical element of this paper is based on the re-analysis of the OfCom Media Literacy survey 2013. This was a quantitative survey comprising 1805 in-home interviews with adults aged 16 and over. Interviews were conducted from October to November 2012. OfCom has conducted a subsequent survey in 2013-14 and prior surveys were undertaken in 2011, 2010, 2007 and 2005[ii]. OfCom media literacy surveys are a nationally representative random sample of UK households. The survey includes over 190 distinct data items covering TV, radio, Internet and mobile media use, attitudes and behaviours. The data also include a substantive range of demographic variables covering, age, gender, ethnicity, class, income, home ownership, location and deprivation. Full details of the data sets can be found on the OfCom website (http://stakeholders.ofcom.org.uk/market-data-research/media-literacy-pubs/).

OfCom provide analyses of the data and year-on-year comparisons in annual reports. These detailed reports include extensive cross tabulations of data and are an invaluable resource to researchers and policy makers. The complexity of the data and the need to provide results for non-technical audiences means that the OfCom reports make limited use of more complex statistical techniques for data reduction and multivariate analysis. This paper therefore explores the issues of class and age by subjecting data on Internet use from 2012-13 to data reduction (exploratory factor analysis), multivariate (MANOVA) and classificatory (cluster) analyses.

Reducing the complexity of the Internet usage data

Within the questionnaire 31 items were identified as measuring types of Internet behaviour. These were items under sections IN14 and IN15 of the survey. They asked respondents if they undertook online activities weekly, quarterly, less than quarterly or never. There are limitations to such a measure. First, it clearly shows its age as many items would likely be done daily if not hourly by very heavy users. Second, some of the categories seem slightly arbitrary and overlap. This may again reflect historic foci and concerns. Having said this, as the following analysis will demonstrate, the measures proved robust enough to provide meaningful and important insights into aspects of digital inequality in the UK. The 31 items were:

- Sending and receiving e-mails
- Using online chat rooms or Instant Messaging
- Buying and selling things online
- Playing games online
- Online gambling
- Banking and paying bills online
- Downloading software
- Maintaining a website or blog/ weblog
- Listening to radio stations online
- Looking at social networking sites such as Facebook, MySpace, Piczo, Bebo, or hi5
- Listen to or download music online
- Watch online or download short video clips such as music videos or comedy clips (e.g. on YouTube)
- Watch online or download TV programmes or films (e.g. BBC iPlayer, 4OD, ITV Player, Sky Player etc.)
- Complete government processes online - such as register for tax credits, renew driving licence, car tax or passport, complete tax return
- Send or receive Twitter updates
- General surfing/ browsing the internet
- Finding information for your work or your job or your studies
- Finding information for booking holidays
- Finding information for your leisure time including cinema and live music
- Finding information about public services provided by local or national government
- Finding information about health related issues
- Looking at news websites
- Looking at political or campaign or issues websites
- Looking at adult-only websites
- Making or receiving calls over the internet (e.g. Skype)
- Doing an online course to achieve a qualification
- Looking at job opportunities
- Visiting dating websites (like match.com, Dating Direct or eHarmony etc.)
- Sign an online petition
- Contact a local councillor or your MP online
- Looking at websites for news about, or events in your local area/ the local community

Factor analysis

The 31 items were therefore subjected to an exploratory factor analysis (EFA) a using principal component method (PCA). Variables were screened for appropriate inclusion in the factor analysis. An initial correlation matrix identified four items that had no significant correlation coefficients above 0.3:

- Looking at adult-only websites
- Visiting dating websites (like match.com, Dating Direct or eHarmony etc.)
- Online gambling
- Doing an online course to achieve a qualification

These items were therefore removed from the analysis. A first run of the EFA using SPSS with PCA, a non-orthogonal Direct Oblim rotation, and Kaisers criterion (Eigen values over 1.0) yielded 5 clear and potentially meaningful factors. Two items were found to have no notable loadings on any of these 5 factors and were removed from the analysis:

- General surfing/ browsing the internet
- Making or receiving calls over the internet (e.g. Skype)

A final analysis using the remaining 25 items was conducted using SPSS and PCA. All items were suitable, having correlation coefficients above 0.3 in the correlation matrix and communalities above 0.3. The Kaiser-Meyer-Olkin value was 0.917, above the recommended value of 0.6 (Kaiser 1970, 1974) and Bartletts Test of Sphericity (Bartlett 1954) was significant (χ 2 (300) = 10408.293, p < 0.000). The diagonals of the anti-image correlation matrix were all over .5, supporting the inclusion of each item in the factor analysis.

The PCA revealed the presence of five factors with Eigen values over 1.0 explaining 28.5%, 8.7%, 5.4%, 4.5% and 4.3% of the variance respectively. An inspection of the scree plot did not indicate a clear break in the reduction of Eigenvalues. This five-factor solution explained a total of 51.5% for the variance. The rotated solution indicated a relatively simple structure showing strong loadings and all but one of the variables loading substantially on only one component (>0.4). The five factors were meaningful and consistent in relation to known forms of digital media use. There was relatively weak correlation between factors (r<0.3) except for factors 1 and 5 (r=0.401) and factors 2 and 4 (r=0.390). These five factors with Eigen values above 1.0 were therefore retained and factor scores were calculated using the Anderson-Rubin method to produce measures that are orthogonal, with a mean of zero and standard deviation of 1. Table 1 provides the pattern and structure matrix results for the analysis.

The five factors and other measures

From the pattern and structure matrices we see that there are five potential Internet behaviours identified by the items. We have named these: *Media consumption*; *Information seeking*; *Political action*; *Formal transactions* and *Social use*. One questionnaire item (Looking at political or campaign or issues websites) loads almost equally on the Information seeking and Political action factors. This makes sense in that such behaviour online could indicate both passive and proactive engagement with such content. It is also reflected in the correlation between Information seeking and Political action. The correlation between *Media consumption* and *Social use* could reflect behaviour by heavy users or specific social groups (e.g. younger people). These issues will be explored in the following sections.

Two other measures were developed using the OFCOM data. A total “breadth of use score” was calculated by summing the responses from all 31 items and transforming to a z-score. An amount of use score was calculated from the sum of the reported hourly use questions in the survey (IN6A, IN6B, and IN6C) converted to a natural log score.

Table 1: Pattern and structure matrix for factor analysis

	Pattern Matrix					*Structure Matrix*					*Communalities*
Factor	**Media**	**Information**	**Politics**	**Formal**	**Social**	**Media**	**Information**	**Politics**	**Formal**	**Social**	
YouTube	**0.709**	0.136	-0.017	0.065	0.107	**0.791**	0.338	0.195	0.283	0.439	0.669
TV or films	**0.696**	0.115	0.075	0.123	-0.014	**0.755**	0.333	0.273	0.312	0.336	0.618
Music	**0.676**	0.007	-0.044	0.104	0.184	**0.762**	0.228	0.145	0.282	0.48	0.628
Games	**0.647**	-0.042	-0.09	-0.082	0.099	**0.643**	0.069	0.034	0.039	0.313	0.438
Radio	**0.493**	0.122	0.234	0.025	-0.039	**0.559**	0.293	0.37	0.2	0.226	0.394
Software	**0.4**	0.035	0.061	0.327	0.177	**0.555**	0.307	0.239	0.479	0.447	0.483
Health Information	0.022	**0.729**	-0.045	0.009	-0.019	0.168	**0.722**	0.151	0.284	0.156	0.523
Public services	0.039	**0.718**	0.063	0.086	0.026	0.238	**0.783**	0.28	0.393	0.242	0.629
News	0.203	**0.644**	0.09	-0.01	-0.042	0.345	**0.699**	0.295	0.285	0.198	0.535
Leisure time	0.152	**0.568**	-0.117	0.093	0.232	0.363	**0.66**	0.113	0.388	0.436	0.554
Holidays	-0.219	**0.515**	-0.117	0.321	0.053	-0.047	**0.573**	0.038	0.473	0.16	0.461
Politics and campaigns	0.055	**0.464**	**0.448**	-0.128	0.065	0.253	**0.559**	**0.567**	0.165	0.218	0.520
Local news	0.092	**0.451**	0.284	0.039	0.037	0.274	**0.57**	0.434	0.295	0.228	0.425
Contact politician	-0.115	-0.049	**0.813**	0.055	0.062	0.081	0.176	**0.794**	0.181	0.128	0.645
Sign a petition	0.132	0.05	**0.641**	0.092	-0.015	0.291	0.28	**0.697**	0.251	0.161	0.519
Banking and paying bills	0.046	-0.006	0.086	**0.782**	-0.095	0.177	0.31	0.226	**0.778**	0.157	0.619
Buying and selling	0.143	-0.064	-0.017	**0.686**	0.093	0.295	0.252	0.135	**0.712**	0.328	0.543
Government processes	0.135	0.199	0.105	**0.585**	-0.183	0.241	0.442	0.27	**0.656**	0.098	0.514
Email	-0.177	0.119	-0.012	**0.499**	0.199	0.023	0.318	0.101	**0.566**	0.297	0.374
Chat and IM	0.122	-0.055	-0.127	0.073	**0.631**	0.35	0.114	-0.019	0.232	**0.671**	0.479
Twitter	0.07	-0.039	0.185	-0.039	**0.622**	0.342	0.154	0.265	0.171	**0.654**	0.467
Job or studies	-0.153	0.271	0.062	0.048	**0.591**	0.166	0.409	0.188	0.304	**0.614**	0.475
Job opportunities	0.129	0.134	0.008	-0.127	**0.582**	0.369	0.251	0.124	0.118	**0.63**	0.434
Social networking sites	0.256	-0.026	-0.132	0.08	**0.539**	0.454	0.152	0.002	0.249	**0.64**	0.477
Website or blog	0.067	-0.148	0.324	0.182	**0.473**	0.327	0.133	0.395	0.332	**0.56**	0.455

Social determinants of Internet use

From the factor analysis and the OfCom data we have eight measures of Internet access and use:

1. Access
2. *Media consumption*
3. *Information seeking*
4. *Political action*
5. *Formal transactions*
6. *Social use*
7. Amount of use (Hours)
8. Breadth of use (Total of all 5 factor scores)

Items 2, 3, 4, 5, 6 and 8 are in the form of a z-score where the sample mean is zero and results are scored as standard deviations from the mean with greater being positive and smaller negative. Amount of use (Hours) is a natural log (ln) score as the distribution correctly skewed toward less use and has a 'long tail' of 'very heavy' users. Item 1 is categorical indicating access in some location or no access at all to the Internet. We will now explore each of these measures against two key social variables – age and class. Social class was split into four groups (AB, C1, C2, DE) using the National Readership Survey social grade classification that is primarily based on employment status (see Table 2). It is interesting to note that the NRS classification was devised for the analysis of analogue (print) media use and consumption. Age was split into three categories 16-34, 35-54 and 55+.

Table 2: NRS social grades

A	Higher managerial, administrative or professional
B	Intermediate managerial, administrative or professional
C1	Supervisory or clerical and junior managerial, administrative or professional
C2	Skilled manual workers
D	Semi and unskilled manual workers
E	Casual or lowest grade workers, pensioners, and others who depend on the welfare state for their income,

If we look at access by combining the main OfCom questions that define access to the Internet (IN1: Has access and use at home, or IN2: mobile or other device access, or IN3: Has access at work or another context such as a UK online centre or library) then we can cross tabulate this with age and social class. The result for age is statistically significant (Pearson Chi-Square= 277.402, df=2, p=0.000) and has a medium to large effect size (Cramer's V = 0.393, p=0.000). Looking at the data it is clear that older people are far more likely to be non-internet users (see Table 3). If we undertake the same analysis for social class groups we get a similar statistically significant result (Pearson Chi-Square= 115.825, df=3, p=0.000) with a medium effect size (Cramer's V = 0.254, p=0.000). In this case we find that 46% of non-internet users are in social class group DE (see Table 4).

Table 3: Age by access to the Internet

*Internet user * Three Age Categories Cross tabulation*				
		Three Age Categories		
		16-34	35-54	55+
Non-internet user	Count	22	67	**335**
	% within Non-internet user	5.2%	15.8%	**79.0%**
	% within Three Age Categories	4.7%	12.5%	**41.9%**
	% of Total	1.2%	3.7%	18.6%
Internet user	Count	444	467	464
	% within Internet user	32.3%	34.0%	33.7%
	% within Three Age Categories	95.3%	87.5%	58.1%
	% of Total	24.7%	26.0%	25.8%

Table 4: Class by access to the Internet

Internet user * Four Class Categories Cross tabulation					
		Four Class Categories			
		AB	C1	C2	DE
Non-Internet user	Count	47	86	96	**195**
	% within Non-internet user	11.1%	20.3%	22.6%	**46.0%**
	% within Four Class Categories	11.5%	16.2%	27.0%	**38.8%**
	% of Total	2.6%	4.8%	5.3%	10.8%
Internet user	Count	361	446	260	308
	% within Internet user)	26.3%	32.4%	18.9%	22.4%
	% within Four Class Categories	88.5%	83.8%	73.0%	61.2%
	% of Total	20.1%	24.8%	14.5%	17.1%

If we look next at total hours on-line we can take the answers to questions IN6A, IN6B and IN6C to calculate an overall score for time spent on the internet in across home, work/school and other locations. This total was converted to a natural log score as the distribution was skewed to the lower values. A two-way between groups analysis of variance across social class groups and age was conducted using SPSS. The data met required assumptions (Levene's test was non-significant). Significant main effects were found for both age ($F(2, 1348)=76.76$, $p=0.000$) and social class group ($F(3, 1348)=17.60$, $p=0.000$) with medium to large effect sizes (partial eta squared of 0.102 and 0.038 respectively). There was no interaction between age and class ($F(6, 1348)=0.532$, $p=0.785$). Undertaking pairwise comparisons within social class group and age we find that all three age categories statistically significantly vary from each other with younger people spending more time on line ($p=0.000$ in all cases using Boneferroni adjustment). In the case of social class group there is a split with social class groups AB and C1 statistically differing from social class groups C2 and DE but not within these two clusters with more affluent groups spending more time online (see Table 5 and Table 6).

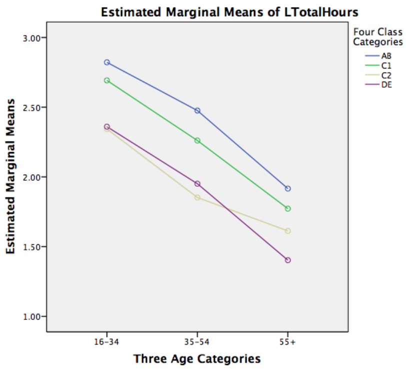
Table 5: Log of total hours by social class

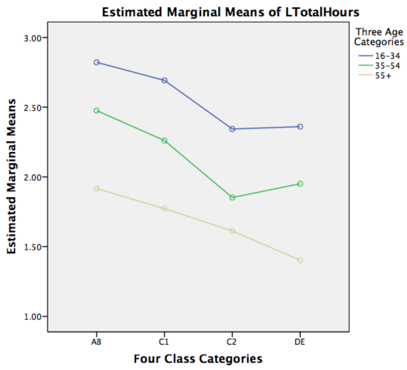
(I) Four Class Categories	(J) Four Class Categories	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
AB	C1	.163	.074	.165	-.032	.358
	C2	.469*	.085	.000	.245	.692
	DE	.500*	.081	.000	.285	.715
C1	AB	-.163	.074	.165	-.358	.032
	C2	.306*	.081	.001	.093	.519
	DE	.337*	.077	.000	.134	.541

C2	AB	-.469*	.085	.000	-.692	-.245
	C1	-.306*	.081	.001	-.519	-.093
	DE	.031	.088	1.000	-.200	.263
DE	AB	-.500*	.081	.000	-.715	-.285
	C1	-.337*	.077	.000	-.541	-.134
	C2	-.031	.088	1.000	-.263	.200

* The mean difference is significant at p<0.005
b Adjustment for multiple comparisons: Bonferroni.

Table 6: Plots of age and class by ln of total use





We next subjected the five factors to a two way MANOVA using SPSS with social class and age as independent variables. Preliminary assumption testing was conducted to check for normality, linearity, univariate and multivartiate outliers, homogeneity of matrices and multicollinearity. Fourteen cases out of 1375 Internet users were found to be multivariate outliers. As variable removal or further transformation was not practical they were removed from the analysis (Tabachnick and Fidell, 2013, p.77). Three variables were found to be significant on the Levene test of Equality of Variances so an alpha level of 0.025 was set for the analysis (Pallant, 2013, p.304). Given these two minor variations to preliminary assumptions Pillais Trace F-test was selected. There was a statistically significant difference between age groups (F(10,1351)=72.9, p=0.000) with a large effect size (partial eta squared = 0.21) and between class groups (F(15,4059)=13.5, p=0.000) with a medium effect size (partial eta squared = 0.05). There was no statistically significant overall interaction between class and age (F(30,6775)=1.4, p=0.079). When looked at separately all factors except Political action presented statistically significant variation by age (see Table 7). When class is considered all factors but Media use presented statistically significant variation (see Table 8). Again there were no statistically significant interactions for each factor using a Bonferroni adjustment to set an alpha level of 0.005.

Table 7: Factors by age

Factor	*df*	*F*	*Sig*	*Partial eta squared*	*Observed power*
Media use	2	155.109	.000	.186	1.000
Information seeking	2	10.214	.000	.015	.987
Political action	2	1.838	.160	.003	.385
Formal transactions	2	25.721	.000	.037	1.000
Social uses	2	329.250	.000	.327	1.000

Table 8: Factors by class

Factor	*df*	*F*	*Sig*	*Partial eta squared*	*Observed power*

Media use	3	.545	.652	.001	.163
Information seeking	3	33.312	.000	.069	1.000
Political action	3	22.317	.000	.047	1.000
Formal transactions	3	34.063	.000	.070	1.000
Social uses	3	14.213	.000	.031	1.000

If we explore each in turn we can identify some specific contrasts within the factors. Exploring pairwise comparisons across age for each factor we find the following (see Table 9). For *Media use* and *Social use* pairwise comparisons between age categories are all statistically significant with younger people undertaking greater use than older people. For *Information seeking* and *Formal transactions* we find that it is only the 55+ age group that shows any statistically significant difference undertaking this activity less than the younger groups. In line with the overall findings there are no statistically significant age variations in *Political action*.

Exploring pairwise comparisons across social class groups for each factor we find the following (see Table 10). For *Media use* there are no statistically significant class pairwise comparisons. For *Information seeking* we find that social class groups C2 and DE do not show statistically significant difference. In the case of *Political action* the situation is more nuanced with social class group AB statistically significantly differing from all others and engaging in substantively more of this type of activity. Social class groups C1 and C2 statistically differ from each other but not from social class group DE. In the case of *Formal transactions* all social class groups statistically differ from each other with higher social class groups undertaking more of this activity. In terms of *Social use* there is a split with social class groups AB and C1 undertaking statistically significantly more of this activity than C2 and DE. These results are graphically presented in Table 11.

Table 9: Pairwise comparisons of factors by age

Dependent Variable	*(I) Three Age Categories*	*(J) Three Age Categories*	*Mean Difference (I-J)*	*Std. Error*	*Sig.[b]*	*95% Confidence Interval for Difference[b]*	
						Lower Bound	Upper Bound
Media use	16-34	35-54	.607*	.061	.000	.461	.753
		55+	1.084*	.062	.000	.936	1.232
	35-54	16-34	-.607*	.061	.000	-.753	-.461
		55+	.476*	.060	.000	.332	.621
	55+	16-34	-1.084*	.062	.000	-1.232	-.936
		35-54	-.476*	.060	.000	-.621	-.332
Information seeking	16-34	35-54	-.096	.065	.417	-.252	.060
		55+	.191*	.066	.011	.033	.349
	35-54	16-34	.096	.065	.417	-.060	.252
		55+	.287*	.064	.000	.133	.442
	55+	16-34	-.191*	.066	.011	-.349	-.033
		35-54	-.287*	.064	.000	-.442	-.133
Political action	16-34	35-54	-.018	.059	1.000	-.159	.123
		55+	-.106	.060	.225	-.249	.037
	35-54	16-34	.018	.059	1.000	-.123	.159
		55+	-.088	.058	.395	-.228	.052
	55+	16-34	.106	.060	.225	-.037	.249
		35-54	.088	.058	.395	-.052	.228
Formal transactions	16-34	35-54	-.006	.065	1.000	-.161	.148
		55+	.399*	.065	.000	.242	.556

	35-54	16-34	.006	.065	1.000	-.148	.161
		55+	.405*	.064	.000	.252	.559
	55+	16-34	-.399*	.065	.000	-.556	-.242
		35-54	-.405*	.064	.000	-.559	-.252
Social uses	16-34	35-54	.725*	.055	.000	.594	.855
		55+	1.418*	.055	.000	1.286	1.551
	35-54	16-34	-.725*	.055	.000	-.855	-.594
		55+	.694*	.054	.000	.564	.824
	55+	16-34	-1.418*	.055	.000	-1.551	-1.286
		35-54	-.694*	.054	.000	-.824	-.564

* The mean difference is significant at the p<0.005 level
b Adjustment for multiple comparisons: Bonferroni.

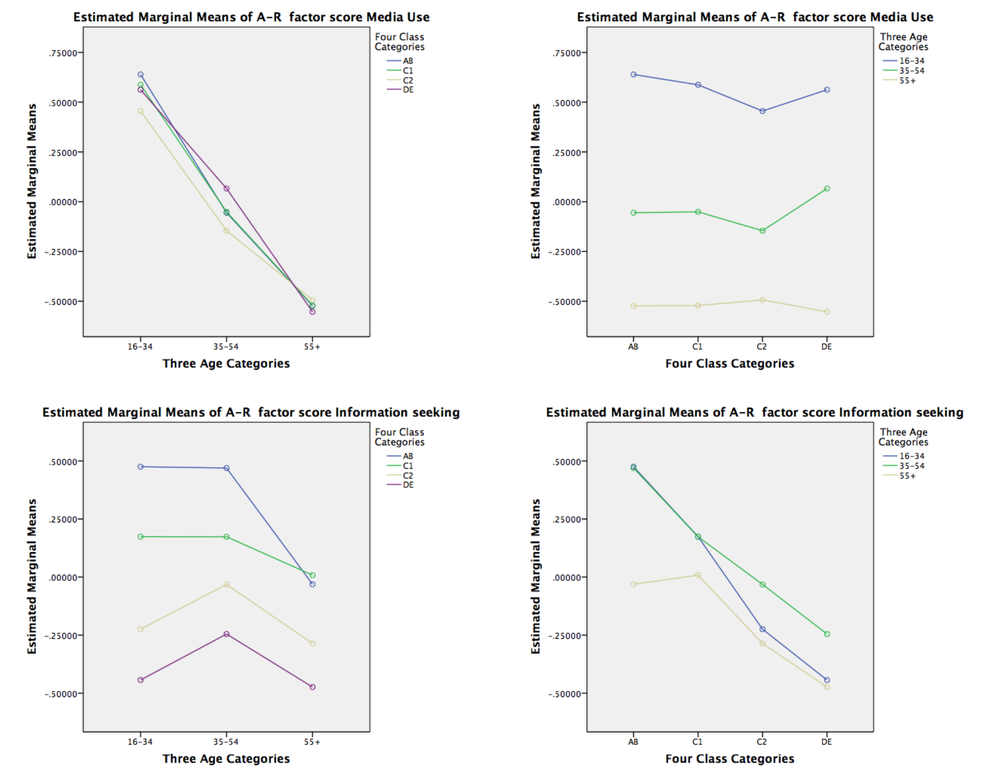
Table 10: Pairwise comparisons of factors by class

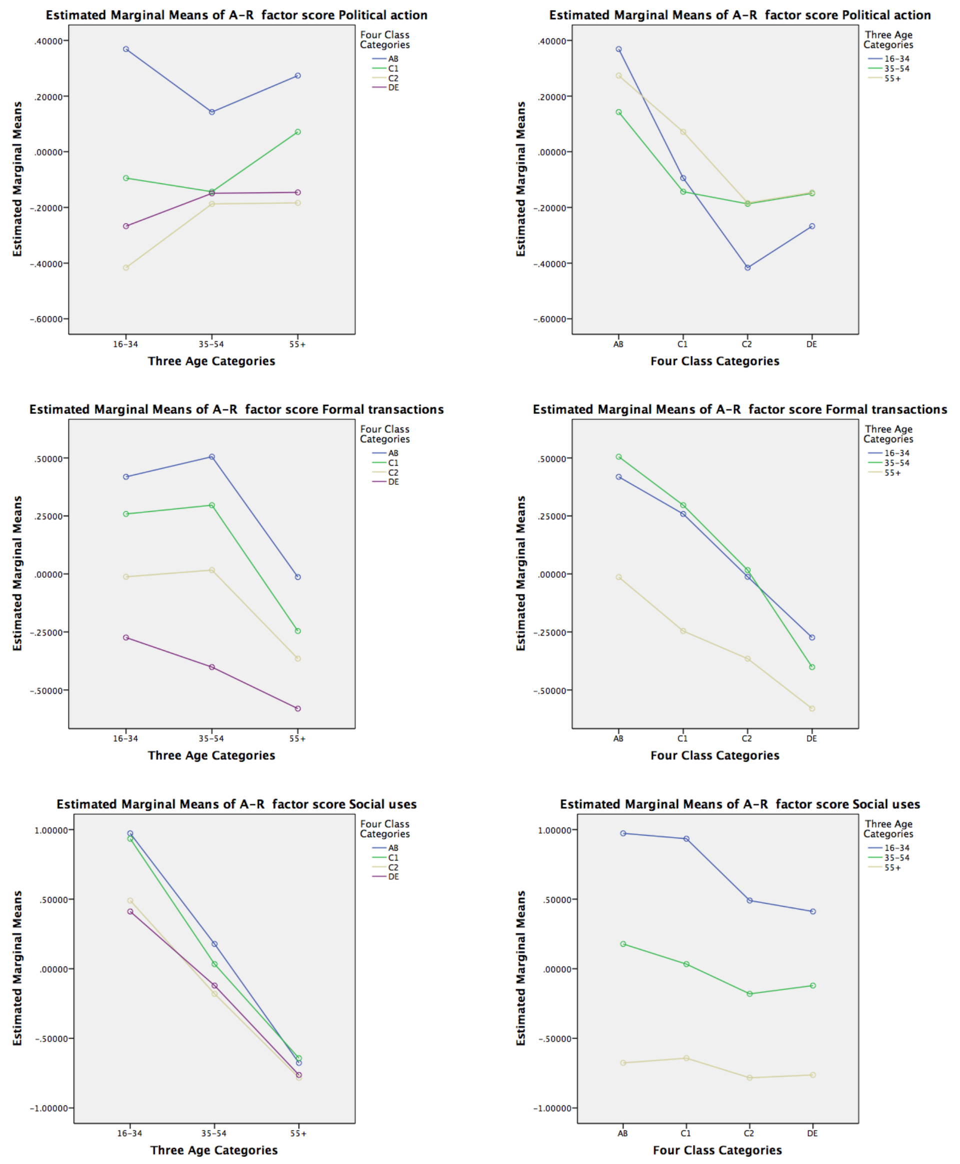
Dependent Variable	*(I) Four Class Categories*	*(J) Four Class Categories*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*[b]	*95% Confidence Interval for Difference*[b]	
						Lower Bound	Upper Bound
Media Use	AB	C1	.015	.064	1.000	-.155	.186
		C2	.081	.074	1.000	-.114	.277
		DE	-.005	.071	1.000	-.192	.183
	C1	AB	-.015	.064	1.000	-.186	.155
		C2	.066	.070	1.000	-.118	.251
		DE	-.020	.067	1.000	-.197	.156
	C2	AB	-.081	.074	1.000	-.277	.114
		C1	-.066	.070	1.000	-.251	.118
		DE	-.086	.076	1.000	-.287	.114
	DE	AB	.005	.071	1.000	-.183	.192
		C1	.020	.067	1.000	-.156	.197
		C2	.086	.076	1.000	-.114	.287
Information seeking	AB	C1	.186*	.069	.042	.004	.367
		C2	.485*	.079	.000	.277	.694
		DE	.692*	.076	.000	.492	.892
	C1	AB	-.186*	.069	.042	-.367	-.004
		C2	.299*	.075	.000	.102	.496
		DE	.506*	.071	.000	.318	.694
	C2	AB	-.485*	.079	.000	-.694	-.277
		C1	-.299*	.075	.000	-.496	-.102
		DE	.207	.081	.065	-.007	.421
	DE	AB	-.692*	.076	.000	-.892	-.492
		C1	-.506*	.071	.000	-.694	-.318
		C2	-.207	.081	.065	-.421	.007
Political action	AB	C1	.317*	.062	.000	.152	.482
		C2	.524*	.071	.000	.335	.713
		DE	.449*	.069	.000	.268	.631
	C1	AB	-.317*	.062	.000	-.482	-.152
		C2	.207*	.068	.013	.028	.385
		DE	.132	.065	.247	-.039	.303
	C2	AB	-.524*	.071	.000	-.713	-.335
		C1	-.207*	.068	.013	-.385	-.028
		DE	-.075	.073	1.000	-.269	.119
	DE	AB	-.449*	.069	.000	-.631	-.268
		C1	-.132	.065	.247	-.303	.039
		C2	.075	.073	1.000	-.119	.269
Formal transactions	AB	C1	.200*	.068	.021	.020	.381
		C2	.424*	.078	.000	.217	.631
		DE	.722*	.075	.000	.523	.921
	C1	AB	-.200*	.068	.021	-.381	-.020

		C2	.223*	.074	.016	.027	.419
		DE	.522*	.071	.000	.334	.709
	C2	AB	-.424*	.078	.000	-.631	-.217
		C1	-.223*	.074	.016	-.419	-.027
		DE	.298*	.081	.001	.086	.511
	DE	AB	-.722*	.075	.000	-.921	-.523
		C1	-.522*	.071	.000	-.709	-.334
		C2	-.298*	.081	.001	-.511	-.086
Social uses	AB	C1	.050	.058	1.000	-.103	.202
		C2	.316*	.066	.000	.141	.491
		DE	.316*	.064	.000	.147	.484
	C1	AB	-.050	.058	1.000	-.202	.103
		C2	.266*	.063	.000	.101	.432
		DE	.266*	.060	.000	.108	.424
	C2	AB	-.316*	.066	.000	-.491	-.141
		C1	-.266*	.063	.000	-.432	-.101
		DE	.000	.068	1.000	-.180	.180
	DE	AB	-.316*	.064	.000	-.484	-.147
		C1	-.266*	.060	.000	-.424	-.108
		C2	.000	.068	1.000	-.180	.180

* The mean difference is significant at the p<0.005 level
b Adjustment for multiple comparisons: Bonferroni.

Table 11: Multivariate plots of factors by age and class





If we combine each usage question into a measure of 'breadth of use', transformed to a z-score itself we can subject this to a two-way between groups analysis of variance across social class groups and age. As Levene's test was significant (p=0.006) a more stringent alpha of 0.01 was set for the analysis. Significant main effects were found for both age (F(2, 1363)=174.70, p=0.000) and social class group (F(3, 1363)=38.59, p=0.000) with medium to large effect sizes (partial eta squared of 0.204 and 0.078 respectively). There was no interaction between age and class (F(6, 1363)=1.507, p=0.172). Undertaking pairwise comparisons within age and social class group we find that all age categories statistically significantly vary from each other (p=0.000 in all cases, using Boneferroni adjustment) with younger people showing the greater variety of use. In the case of social class all groups statistically differ from each other except social class groups C2 and DE with more affluent groups using the internet in more varied ways (see Table 12).

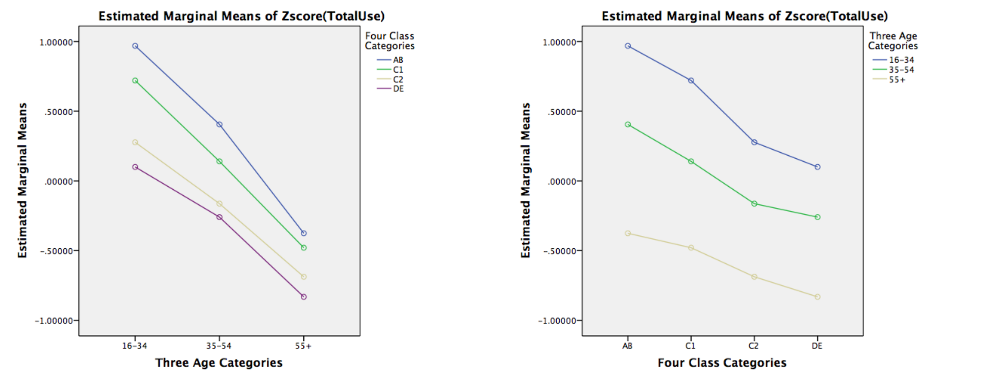
Table 12: Pairwise comparison of total varied use by class

(I) Four Class Categories	(J) Four Class Categories	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower	Upper

					Bound	Bound
AB	C1	.206*	.062	.006	.041	.370
	C2	.524*	.071	.000	.336	.712
	DE	.663*	.069	.000	.482	.844
C1	AB	-.206*	.062	.006	-.370	-.041
	C2	.318*	.068	.000	.139	.497
	DE	.457*	.065	.000	.286	.628
C2	AB	-.524*	.071	.000	-.712	-.336
	C1	-.318*	.068	.000	-.497	-.139
	DE	.139	.074	.352	-.055	.333
DE	AB	-.663*	.069	.000	-.844	-.482
	C1	-.457*	.065	.000	-.628	-.286
	C2	-.139	.074	.352	-.333	.055

* The mean difference is significant at the p<0.005
b Adjustment for multiple comparisons: Bonferroni.

Table 13: Plots of total varied use by age and class



Initial conclusions

What can we conclude from these initial analyses? First, those older and less affluent citizens remain far more likely to be digitally excluded in terms of material access. This is clearly indicated in Table 3 and Table 4. Second, age *and* class are found to *separately* have medium to large effects on both the amounts *and* types of Internet use. Third, in all cases class and age do not interact but operate as separate predictors. In other words there is no statistical evidence for class and age exacerbating or mitigating the effects of the other variable.

Some specific differences are noteworthy. The 55+ age group stands out as differing more from the younger two groups on a certain measures such as *Information seeking* and *Formal transactions*. Also a number of analyses point to a general split along class lines with AB and C1 as a group often differing from C2, and DE. We can summarise these results by looking at the areas of intersection between class and age where scores are above or below average (z-scores greater than or less than zero). These are presented in Table 14, which clearly indicates the overall finding that in general younger more affluent citizens are greater users of the Internet. The patterns in Table 14 also illustrate the importance of age to variations in *Social* and *Media use,* and the role of class in *Information seeking* and *Formal transactions*.

Table 14: Score above and below the mean

	Mean Z-scores	Total Use	Total Hours	Media Use	Information seeking	Political action	Formal transactions	Social uses
16-	AB	**0.969**	**0.616**	**0.652**	**0.465**	**0.469**	**0.394**	**0.978**

34								
	C1	**0.720**	**0.497**	**0.621**	**0.217**	-0.021	**0.300**	**0.944**
	C2	**0.277**	**0.179**	**0.483**	-0.204	-0.274	0.004	**0.517**
	DE	0.100	**0.194**	**0.556**	-0.415	-0.268	-0.274	**0.433**
35-54	AB	**0.405**	**0.300**	-0.031	**0.474**	**0.210**	**0.490**	**0.186**
	C1	**0.140**	**0.103**	-0.044	**0.171**	-0.111	**0.295**	0.045
	C2	-0.163	-0.270	-0.146	-0.032	-0.187	0.017	-0.180
	DE	-0.260	-0.180	0.066	-0.245	-0.149	-0.401	-0.121
55+	AB	-0.375	-0.211	-0.523	-0.002	**0.392**	0.020	-0.670
	C1	-0.479	-0.343	-0.515	0.009	0.074	-0.241	-0.644
	C2	-0.687	-0.489	-0.494	-0.286	-0.184	-0.365	-0.783
	DE	-0.831	-0.680	-0.553	-0.474	-0.146	-0.581	-0.763

Colour grading in 5% percentile grades from minimum (red) to maximum (green)

The lack of an interaction between age and class, and the fact that some types of behaviour are explained only by one of these variables (e.g. *Media use* and *Political action*), implies that assumptions around changing age demographics and digital engagement have to be challenged. It leads to the conclusion that any simple assertion that issues of digital exclusion, inequality or difference are likely to disappear as the population ages may not be supported by the evidence. Though more longitudinal work is needed to absolutely confirm this.

Understanding class, age and user types

Internet use does not take place in isolation and overall breadth or level of use masks the complex mix of behaviours that any one individual or group may undertake. In order to explore this we subjected our five factors to a cluster analysis to see if the data provided evidence of behavioural groupings within the survey sample. As there is no clear premise upon which to assume a likely number of groups within the data the analysis undertook a two-step approach to clustering the data. The first step used a standard hierarchical cluster analysis under SPSS. As the factors were z-scores a squared Euclidean distance measure of cluster separation under Wards clustering method was used. Looking at the final ten steps of the analysis clear breaks in the rate of change of the cluster coefficient scores were noted at two, four and seven clusters. Descriptive analysis of the means for a two-cluster solution indicated that the clusters separated limited users from the rest of the sample. Seven clusters provided a more informative set of user types than four and is therefore used here. The cluster analysis was therefore re-run with the k-means cluster technique applied to the data with a target of seven clusters and iterations repeated until results converged. Table 15 presents the mean z-scores for our five factors at the centroids of the clusters and potential descriptors for these groups.

Table 15: Seven potential user type clusters

	Cluster						
Factor mean z-scores for cluster centroids	1	2	3	4	5	6	7
Media Use	-0.638	1.122	-0.693	0.899	0.775	0.465	-0.750
Information seeking	-0.698	0.505	-0.851	-0.460	0.946	0.804	0.801

Political action	-0.327	-0.016	-0.181	-0.501	2.889	0.465	-0.422
Formal transactions	0.561	0.795	-1.154	-0.691	0.711	0.631	0.169
Social uses	-0.328	1.275	-0.781	0.458	0.980	-0.722	0.035
Potential descriptor	**Formal transaction limited user**	**Non-political extensive user**	**Limited user**	**Social media users**	**Political extensive user**	**Non-social media general user**	**Information seeking limited user**

These two results present us with inductively defined typologies of Internet usage behaviour that we can compare against our social class group and age variables. Chi-square analyses for the seven clusters across class and age were undertaken, yielding significant results in all cases with medium effects (see Table 16)

Table 16:Analyses of cross tabulations of clusters by class and age

Cross tabulation	*Chi square results*
Seven user types (clusters) by social class group	Pearson Chi-Square=132.345, df=18, p=0.000, medium effect size (Cramer's V=0.179)
Seven user types (clusters) by age	Pearson Chi-Square=103.960, df=9, p=0.000, medium effect size (Cramer's V=0.159)

If we look at the distribution the ‘seven user type clusters’ by age and class a nuanced picture emerges. The majority of people aged 16 to 34 are ‘Social media users’ or ‘Non-political extensive users’. The majority of people over 55 are again ‘Limited users’ the remainder being evenly split between ‘Non-social media general users’, ‘Information seeking limited users’ and ‘Formal transaction limited users’. The 35 to 55 year old age group is reasonably evenly spread across all user types – though ‘Political extensive users’ is a minor grouping for all age ranges.

Looking at class we find that social class group AB has the highest proportion of ‘Political extensive users’, the lowest proportion of ‘Limited users’ and the lowest proportion of ‘Social media users’ and a relatively even distribution of other user types. Conversely social class group DE has the highest proportion of ‘Limited users’ and the highest proportion of ‘Social media’ users. In other words there is greater variety of users in social class group AB and more limited variety of users in social class group CD. The other categories are fairly evenly distributed but show lower proportions than found in other class groups. A graduated transition from AB to DE (or vice versa) can be seen in the graph. If we add the non-users as an eighth group, those without access and not included in the factor analysis, we see a very clear pattern in which over 50% of both social class group DE and of older users are either not online or are limited users (see Table 17 and Table 18).

Table 17: Plots of the proportions of the 7 user type clusters by age and class

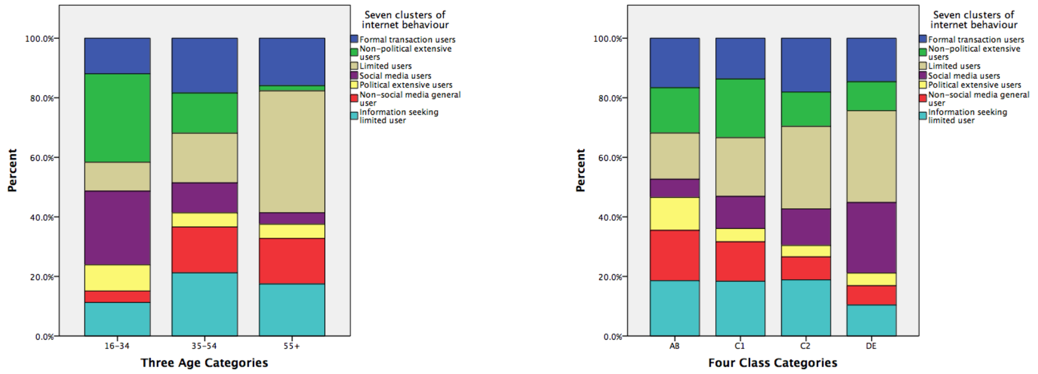
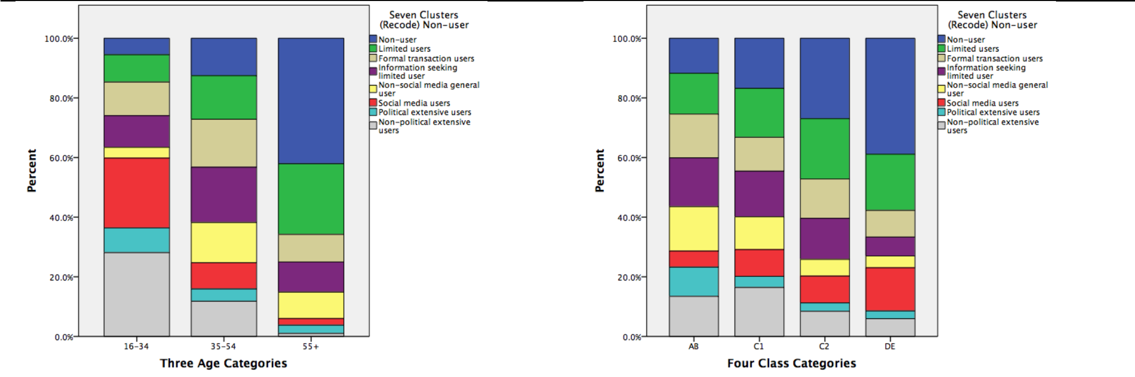


Table 18: Plots of the proportions of the 7 user types plus non-users by age and class



Discussion

We would argue that the data presented here provide some key reference points for both academic study and policy development. First, class and age remain predictive variables in relation to access to the Internet as well as levels, types and breadth of use. Second, class and age are variables that produce medium to large effects in these measures of access and use. Third, class and age do not interact in any of the analyses. In other words though class group DE and age group 55+ are less likely to use the Internet, there is no multiplied compounding of inequalities through age and class reinforcing each other. Put another way, if age is held ‘constant’, then class related inequalities are not statistically affected and vice versa. As a result even if predications that age effects will disappear over time prove correct, we cannot assume that class based ones will.

If we look at types of use we find notable class and age variations within types of use. With some, such as *Media use*, being solely age determined and others, such as *Political action*, being solely class determined. When we combine patterns of use into user types we find notable age and class variations in the proportions of user types. Importantly we see a greater breadth of use and a more varied set of user types in class group AB and far more limited use in class group DE. We may be able to infer life stage and social context explanations for these variations. Though such a conclusion would require additional detailed longitudinal and qualitative work, we believe these results point to two key issues. First, class is a proxy for multiple aspects of inequality and difference that are driven primarily by socio-economic factors. Therefore, we should not be surprised to find that many aspects of both digital media access and use reflect these longstanding social structures. Second, age and class reflect aspects of both life-stage and life-worlds. This is reflected in this analysis by the fact that consumption of digital entertainment media (*Media use*) is driven by age and digital politics (*Political action*) is driven by class.

We can clearly conclude that citizens who are online make use of the Internet, but not in ‘conditions’ of their own choosing (to abuse a well known phrase). The data analysis here point to potential long term gaps in economic, social and cultural capital driven by the fact that the *full variety* of Internet use is predominantly limited to the wealthiest citizens. We would reiterate the point that those with the least access, who are making the least use and least varied use of the Internet, are older adults or those in social class group DE. What the long term social and personal impacts of this inequality will be have yet to be fully explored. Though citizens do not need to engage with the full breadth of the Internet to utilise "digital by default" services, it is clear from this analysis that the majority of likely service users have limited access and usage levels. More broadly the educational, social and financial benefits of ICT use are more likely to require a broader use of the Internet.

Getting the balance right in both the research and policy agenda for digital inclusion is no longer simply about closing 'knowledge or information gaps' to support citizens. The 'digital-by-default' agenda puts digital inequalities centre stage in the provision of support for key socio-economic groups. These class and age measures capture a vast array of life stage, contextual, economic and personal factors. These factors need to be understood in the context of the broader social inequalities they also imply if effective support for these citizens is to be provided, and if the implementation of 'digital-by-default' is to be undertaken without adding to these inequities.

Conclusion

We would argue that the analysis presented here indicates clearly that though age remains the main predictor of levels of internet use this should not be read as indicating issues of access and digital inequality will disappear over time. Class remains a key predictor of the same measures and there is evidence that within both class and age there are variations that point to greater complexities based on life-stage, life-world and the integration of digital media use into issues of social and cultural capital. Any policy developments based on assumptions of long term ubiquity and equity in both access to and uses of digital media have therefore to be questioned.

Support

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[ii] The research team were provided full access the data as part of the joint 'Socio-digital' research and knowledge exchange network run by the Tinder Foundation. We therefore thank both Tinder and OfCom for providing the network and access to the data.