Who are the limited users of digital systems and media? An examination of UK evidence.

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Citation:

YATES, Simeon, CARMI, Elinor, LOCKLEY, Eleanor, PAWLUCZUK, Alicja, FRENCH, Tom and VINCENT, Stephanie (2020). Who are the limited users of digital systems and media? An examination of UK evidence. First Monday, 25 (7). [Article]

first monday
PEER-REVIEWED JOURNAL ON THE INTERNET

Who are the limited users of digital systems and media? An examination of U.K. evidence

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Abstract

This paper presents findings on the correspondence of levels of digital systems and media use with a range of socio-economic and demographic measures in the U.K. Most research on inequalities in regard to digital systems and media has focused on access and skills. Building on prior work (Yates and Lockley, 2018; Yates, *et al.*, 2015) we argue that inequalities in regard to digital systems and media are better understood around types of user and their correspondence to other key social variables — rather than solely individual skills and access. The analysis presented here covers a range of key demographic variables, especially those that are markers of distinct social disadvantage. We find that those not using the Internet have distinct characteristics — predominantly around age, education and deprivation levels. We also find that those undertaking limited uses (overall limited use or a very narrow range of uses) are all predominantly from lower socio-economic status backgrounds with variations due to age and education. The data used for the analysis is the recent U.K. Ofcom 2018–19 (n = 1,882) media literacy survey. The paper uses latent class analysis methods to inductively define user types. Multinomial and binary logistic regression are used to explore the correspondence of latent class group membership to key demographic variables. These insights have direct U.K. and international policy relevance as they are key to the development of strategies to tackle ongoing digital inequalities in U.K. society.

Contents

1. Introduction

It has become very clear that the ‘digital divide’ is not simply between those who are ‘off-line’ and ‘online’ but must also consider those who use digital systems for limited purposes or have only limited digital skills. Having said this, much government and charitable sector policy remains focused on those who are “off-line” (non-users). There also remains an assumption that once citizens have obtained access to digital systems and media or digital skills that they will continue to remain “users”. However, evidence from both the U.K. and U.S. (see various Ofcom [1] and Pew [2] surveys) indicates that access can vary over different timescales. For example, within a medium-term timeframe access might be lost due to the costs of mobile data or ISP access being too high and termination of contracts. Longer term current users may cease to use some or all digital systems at key life stages, especially post-retirement, with skills therefore becoming obsolete as technology changes. As we will note below and has been noted in other studies (Anderson, *et al.*, 2019) the intersection of key demographics of age (both young and older groups), income (especially poverty or deprivation) and education can all underpin limited use of digital systems and media.

In this paper we seek to explore the underlying demographic characteristics of limited users of digital systems and media in the U.K. We draw on recent survey work by Ofcom (2019), the U.K. media regulator, as part of its ‘Making Sense of Media’ programme. We take an inductive and relative statistical approach to defining ‘limited users’, exploring the key demographics that underpin the groups we identify. The paper begins with an overview of recent work on digital inequalities so as to highlight key demographic variables or issues that the analysis will then explore. We then present our inductive analysis and definition of user types. This is then followed by various statistical models and comparisons of the different user types utilising the identified key demographic variables. The paper concludes with a discussion of the findings, and their potential policy relevance.

2. Forms of digital inequality

2.1. Digital inequalities in access, levels and types of use

To date the majority of research on digital inequalities has focused on three issues. First, inequalities and divides in terms of material access, mostly in terms of having access to computers and Internet connection. Second, divides and differences in levels of skills [3] and uses, for example, the ability to write and send an e-mail message. Third, more recent work has been concerned with differences in 'tangible' outcomes (van Deursen and Helsper, 2015). A broader fourth position that considers the correspondence of digital inequalities (however measured) to other aspects or 'fields' of inequality has also developed (Helsper, 2012; Yates*et al.*, 2015; Yates and Lockley, 2018). When discussing the first area of access to digital services and media — especially Internet access — research has often constructed this in terms of a 'divide' as Jaeger, *et al.* note about the U.S. context:

> "... the gap — whether based in socio-economic status, education, geography, age, ability, language, or other factors — between Americans for whom Internet access is readily available and those for whom it is not." [4]

Very often this issue of absolute access to resources (computers, Internet access, information) has remained a key focus of policy, but it has long been noted that differences and inequalities are broader and more complex than just access. In terms of the second area, Hargittai (2001) points out the need to address more nuanced measures than the binary one of access or no access. Hargittai proposed focusing on citizens' differences in levels of skill in finding information online considering:

> "... variation on five dimensions: differences in the technical apparatus people use to access the Internet, location of access (*i.e.*, autonomy of use), the extent of one's social support networks, the types of uses to which one puts the medium, and one's level of skill." [5]

Hargittai has importantly included how people's social networks and support play a key role in their ability to gain digital skills. Adding to this discussion, van Dijk and Hacker (2003) have identified that digital divides are also about relative differences between categories of people. According to them, the digital divide derives from a:

> "... usage gap, not primarily based on differential derived knowledge or information but on differential practical use and positions in society." [6]

In this way, people's social and cultural capital will have an impact on people's ability to use digital tools and services. In the context of the Netherlands, van Deursen and van Dijk (2014) have more recently documented clear socio-economic variations in usage patterns similar to those identified in the U.K. (see Yates, *et al.*, 2015; Yates and Lockley, 2018). Similar results are found in the U.S. with most recent Pew Research Center 'fact sheet' noting that "adoption gaps remain based on factors such as age, income, education, and community type" (Pew Research Center, 2019). Importantly, for this study we would note that many of these approaches focus on non-users (those not on the Internet), rather than limited or narrow users. Ignoring these groups may miss people who are nominally deemed online but nevertheless need attention and a different policy approach.

Inequalities in digital *skills* have also been debated by scholars (van Deursen, *et al.*, 2014; Helsper, *et al.*, 2015) and policy-makers (United Nations High-level Panel on Digital Cooperation, 2019). In their analysis of digital skills measurement, van Deursen, *et al.* (2014) argued that both digital and social skills should be considered in the multiple contexts of online activities (*e.g.*, personal, economic, cultural and social). To further develop this analysis of citizens digital skills, they propose the examination of the 'tangible outcomes' of Internet use. As stated by Helsper, *et al.*: "To understand the importance of the Internet, we need to focus on the tangible — or 'real' — outcomes that digital divide policies can address." [7]

The importance of an improved analysis of digital inequalities has also been highlighted by international policy-makers. The recent report of the United Nations' High-level Panel on Digital Cooperation (2019) suggests that further work is needed to not only systemise and improve digital inclusion evaluation but examine the 'real-world' impacts of e-participation. As these approaches show, there is a need to go beyond the traditional 'access only' framework to tackle the digital divide in a way that is meaningful to wide varieties of people. In this paper we are therefore looking to explore the social context of those citizens who are limited or "narrow" users of digital systems and media.

2.2. Broader context of digital inequality

Where prior work has examined types or levels of use, approaches often focus on individuals' skills and uses. Such a focus is key for many areas of policy intervention, but we are drawing on the fourth area noted above and Helsper's (2012) argument that digital inequalities have to be understood as being in correspondence with other 'fields' of social, cultural and economic inequality. We have previously argued that differences and inequalities in digital systems and media use need to be understood in relation to individuals available social, cultural and economic capital and the embedding of digital within their habitus or 'lifeworld' (Yates and Lockley, 2018; Yates and Lockley, 2020b). This paper follows this strand of the debate to explore in greater depth those citizens who are making *limited* use of digital systems and media — in terms of either absolute levels of use or range of uses (*e.g.*, only using social media). Though the data analysed here does not measure tangible outcomes, clear correspondences between digital media use and socio-economic position and cultural capital can be identified.

This broader position can also be used to reset the conceptualisation of inequalities in digital systems and media use away from the idea of "users'" individual access, skills to a broader understanding of digital as part of citizens' networked and community lives. The focus on *citizens* resets the question to one of how people and groups are active in their social contexts, much of which may now be permeated by digital systems even if they are not users themselves. One does not have to be a Facebook user to have information about them or have images of them posted online.

This paper follows on from two prior analyses (Yates, *et al.*, 2015; Yates and Lockley, 2018) that have linked levels and types of Internet use to key social, economic and cultural factors, and which have highlighted the correspondence of social class using data collected in 2013 and 2016. Here we explore more recent data collected by Ofcom in 2018 (Ofcom, 2019) and focus specifically on the demographic characteristics of those citizens who are more limited users of digital systems and media. Though of course, addressing non-use of digital services and media remains a key concern for policy-makers in the U.K., as well as globally where developing routes to access remains a primary focus (Arora, 2019).

Insights over the past five years have found that the proportion of non-users in the U.K. — those not using the Internet — has remained stable at around 14 percent (Ofcom, 2019). We will demonstrate that non-users are predominantly older people with lower levels of educational attainment, who are more likely to be in deprived circumstances, and to have previously held lower socio-economic status employment. The persistence of this group and its stable size implies that this may reflect a 'life stage' rather than a cohort effect. This is backed by recent findings from the Oxford Internet Survey (Blank and Dutton, 2019). As their report notes:

> "Internet use has expanded in all age groups, although the increase is small over the past 6 years. The notable pattern is that almost everyone is online up to about the age of 50. After 50 there is a sharp decline in Internet use of about 2 percentage points per year." [8]

These findings contradict prior and some current policy positions (*e.g.*, Yiu and Fink, 2013) which had argued that the non-user group would decline over time as younger more digitally engaged cohorts aged. Age, therefore, remains a significant factor when it comes to non-use of digital services and media. We will return to these issues in our final discussion.

In undertaking the analysis below we are concerned to show that digital inequalities are not solely about access, skills and outcomes. Though there is a straightforward and understandable logical chain from access via skills to outcomes, this is a model embedded in a very 'technology' and individual 'user' focused view of digital systems and media. Whereby the challenge is one of accessing and mastering the technology. In fact, as many contemporary qualitative studies (Robinson, 2011, 2009; Robinson, *et al.*, 2015) have indicated levels and types of digital systems and media use is closely linked to social, economic and cultural context. Even where there is access, the types of use vary greatly and skills may be highly correlated to context (Yates and Lockley, 2020a). Indeed, it is potentially the case that skills do not shift domains, such as from personal use (*e.g.*, Facebook) to workplace (*e.g.*, Excel) or even use of the same systems for civic action (*e.g.*, community engagement) (Yates and Lockley, 2020a).

This view fits with more recent qualitative work by Scheerder, *et al.* (2019), who examine digital inequality from a domestication approach. Looking to explore issues more deeply than their prior quantitative studies, they undertook 48 interviews with families in the Netherlands. In particular, they considered the development of 'what technology means' to users and non-users and how it is immersed in their daily life. The technology domestication approach provides explanations for how individuals integrate new technologies into their particular social context (Haddon, 2011, 2006). Scheerder, *et al.'s* analysis indicates that less educated families are less interested in Internet developments and tend to have a less reflective stance. Whereas higher educational attainment families took a more critical stance to digital systems and media. Scheerder, *et al.* make a similar argument to Yates and Lockley (2018) making an important link back to broader conceptions of social class and inequality though the use of Bourdieu's concept of habitus:

> "The observed differences between LEA [lower educational attainment] and HEA [higher educational attainment] can be considered in light of the concept of information habitus (Bourdieu, 1980; Robinson, 2009). Habitus refers to the mental structure that individuals develop during their life, while growing up in a particular social environment.

> Individuals with a corresponding social background, as shaped by educational level, will develop a similar habitus and correspondingly act on it. HEA-members adopt a stance or habitus of 'studious leisure', which results in consciously exploring possibilities and benefits that the Internet has to offer." [9]

Though we have concerns about attempts to differentiate "digital" or "information" capital from the core ideas of economic, social and cultural capital of Bourdieu's theory (see Yates and Lockley, 2020b), such work highlights the important link between education (cultural capital) and forms of engagement with digital systems and media — context matters. These engagements clearly form part of contemporary cultural capital and its manifestation in contemporary habitus.

Similarly, Rhinesmith, *et al.* (2019) have examined how different groups frame the value of broadband in their everyday lives including the strategies that low income citizens use to achieve access to high-speed broadband. They argue that:

> "... the Internet is relevant to low-income people, but because of the high-cost of fixed broadband, they often rely on a broader social infrastructure, or an ecology of support, to help them gain access to computers and the Internet in ways that reflect their everyday experiences." [10]

They detail how citizens practice what they call "broadband workaround activities" such as splitting the bills with neighbours or going to the libraries in order to access broadband. Ultimately, Rhinesmith, *et al.* (2019) argue that although digital literacy is an important factor, cost remains a central factor for 'non-adopters' of high-speed broadband.

When discussing the cost factor, we need to consider how many people from low-income communities use smart phones as their main access point. A key recent trend identified in the Ofcom's media literacy data is the growth of smart phone or smart device only access to digital systems and media. As we will note below, there is also a strong link between being smart device only users and limited digital systems and media use. In relation to this, a recent study by Fernandez, *et al.* (2019) using both survey and focus groups methods explored the detail of users lives within three communities in Detroit (Michigan, U.S.) chosen to reflect variation in the socio-economic make-up of the city. Fernandez, *et al.* argue that the uses of digital technologies in such "low-income, distressed communities" is more complex than simply one of 'non-use' or a lack of interest in using the Internet. As, they argue, the majority of members of such communities seek various types of solutions to getting online. The major distinction they find is between those with broadband ISP service and those with mobile only access. They noted that:

> "A second divide emerged in the form of relatively greater dependence on mobile phones, and the limitations of mobile devices when compared to, or used in combination with, home devices like desktops and laptops. Survey data indicated that mobile phones were central to the information ecosystem in Detroit. Almost four-fifths (79%) said they access the Internet on handheld devices ... ." [11]

The research found that age was a key predictor of mobile only dependence, but importantly that cost was a key barrier to uptake of ISP service. They also noted that many respondents struggled with costs for both ISP and mobile data plans leading to intermittent access, noting that:

> "Many [respondents] experienced service disruptions because of unpaid phone bills or having to pay extra for exceeding data caps ... 30% of those with cellphones reported having stopped service at some point due to cost. These trends illustrate the instability associated with mobile Internet access and highlight the importance of having multiple access points to go online ... paying cellphone bills often creates a financial strain that can interfere with other essential bills and services. Focus group participants admitted to delaying, avoiding, or cancelling other important services and necessities in order to pay for home Internet or data plans." [12]

Fernandez, *et al.* provide a rich description of people who might be considered 'limited users' of digital systems and media. This does not mean they are antithetical to digital media use or do not see the value of it, far from it, they are often seeking innovative solutions to being online. The limitations of mobile (smart) devices, forms of access, skill and education levels combined to collectively limit overall levels and types of use. Importantly, Fernandez, *et al.* point out that some views of the activities of limited users — that they only engage with entertainment or social media — misses the point that such uses might reflect the contexts of access and limitations of devices being used (Fernandez, *et al.*, 2019). In this paper we therefore seek to explore the key demographics and features of limited users of digital media and systems. A key element of that being which devices and methods they use to interact with digital media. As a next step we define 'limited users' and how we will examine these in our analysis.

2.3. Defining 'limited users'

In this paper we take an inductive approach to defining limited users. It follows a similar approach taken in prior papers (Yates, *et al.*, 2015; Yates and Lockley, 2018) and makes the following assumptions:

- Limited use of digital systems and media is relative to overall patterns in the whole population.
- Limited use can be in terms of absolute low levels, that is low probabilities of use across all types of digital use, or in terms of a limited variety of uses.
- Limited use should not be defined by researchers or policy-makers who may over value specific types of use over others (*e.g.*, uses for education and training). Here we want to distance ourselves from the ideological position that some scholars and policy-makers take when defining what are the 'valuable types of use' — positions that ignore citizen's everyday contexts, needs and practices..

2.4. Research questions

From the literature discussed above we have identified eight key demographics where we wish to explore their correspondence with limited use:

1. Age — this appears as a key factor in most prior work and policy work.
2. Social class (socio-economic status) — as a measure of both economic capital and also relative social or employment status.
3. Educational attainment — as a measure of engagement with both formal education and skills (a proxy for cultural capital).
4. Deprivation — as a measure of relative economic capital and economic context.
5. Employment/Retirement — as a measure of economic activity.
6. Household composition — as a measure of life stage and the presence of children in the household.
7. Urban/Rural — given the policy concerns over rural access.
8. Health — especially chronic conditions that impact everyday life.

From these areas of focus we have developed the following research questions:

- *RQ1*: What groups do current citizens fall into as defined by their levels and types of digital systems and media use? This will be addressed through the use of latent class analysis.
- *RQ2*: How are these groups differentiated against each other by key demographic variables — which demographics correspond most closely with latent class membership? This will be addressed through multinomial regression.
- *RQ3*: What are the specific demographic markers of those latent classes we identify as limited users of digital systems and media? This will be addressed through binary logistic regression.
- *RQ4*: How do they key demographics individually correspond to latent class groups? This will be addressed through χ^2 contingency tables.

In our discussion of the analytic results we have highlighted two groups of users that need further research examination. First, those with an overall low probability of use across all activities. Second, those whose use is limited to social media and entertainment media. In both cases there is a strong correspondence with levels of deprivation.

3. Methods

This section sets out the data sets, statistical software and statistical methods employed in the analysis.

3.1. Data sets

For this research we used the Ofcom Adults Media Literacy survey, which is an annual nationally representative sample of U.K. adults aged 16 and over. The 2018–19 (n = 1,882) survey used here was conducted by Critical Research in-home using a Computer Aided Personal Interviews methodology between September and October 2018. The Ofcom data provides one of the most extensive surveys of U.K. Internet behaviour across both levels and types of digital media use.

3.2. Statistical approach

The following analysis was conducted in three stages. First, Internet users were categorised using latent class analysis according the probabilities of undertaking a range of behaviours online from paying bills to social media use. Second, we look at the characteristics of non-users and limited users by utilising binary regression and multinomial regression methods. Third, we consider the specific relations between key variables using contingency tables and χ^2 tests. The analyses presented here were undertaken using R (version 3.6.1) running via RStudio (version 1.1.442) under MacOS (version 10.14.6).

Our prior approach to classifying Internet users from the Ofcom data sets used an initial factor analysis and factor scoring of users behaviours, followed by a cluster analysis of the factors scores (see Yates, *et al.*, 2015; Yates and Lockley, 2018). As a result of changes to the Ofcom survey, predominantly to deal with the shift to greater social media use and the rise in digital media consumption (TV/Film and Music/Radio), this approach is no longer possible. Though some variables remain the same, others have been expanded and the majority are also now clearly categorical (nominal) rather than ordered (ordinal). For example, there has been a shift from measuring rates of behaviour as "weekly; monthly; yearly" to "in the last week; in last three months; ever". As a result, we now employ latent class analysis (LCA) as a route to classifying the Internet user types.

LCA is a subset of structural equation modelling, used to find groups or subtypes of cases in multivariate categorical data. A latent class is distinguished by a pattern of conditional probabilities that indicate the chance that each variable will take on certain values. LCA therefore looks to generate a set of 'classes' that best predict the probability that categorical measures such as 'yes/no' or 'once/twice/more' appear together. LCA can then assign cases to groups (latent classes) according to those probabilities. In this sense LCA is analogous to factor analysis where latent classes have a similar role to factors — though cases and variables (not just variables) are allocated to classes. LCA can therefore be viewed as identifying the underlying (latent) groups of people (classes) with statistically similar results. Importantly, unlike other alternative methods such as the majority of cluster analyses, LCA provides overt criteria (minimum Bayesian information criterion (BIC) score) for selecting the optimum number of classes (see Nylund, *et al.*, 2007).

For the current analysis we used the poLCA package (version 1.4.1) (Linzer and Lewis, 2011) and utilised code based on the example provided by Ohlsen (2015). Regression analyses were undertaken using R with the logistic regression being run using the binomial family 'logit' options of the glm() function. The multinomial regression was undertaken using the multinom() function of the nnet package. In the next section we present our analysis and results.

4. Analysis and results

4.1. Latent class analysis

To mirror as closely as possible the prior analyses in Yates, *et al.* (2015) and Yates and Lockley (2018) we selected the following variables from the Ofcom Media Literacy data set:

1. News: Access news Web sites or Web sites about politics or current affairs.
2. Politics: Signed an online petition or used a campaigning Web site such as change.org.
3. Government process: Complete government processes online — such as update Universal Credit (https://www.gov.uk/universal-credit), renew a driving licence or passport.
4. Council tax: Pay online for your council tax or for another local council service (parking ticket, congestion charge etc.).
5. Public services: Look online for public services information on government sites such as nidirect (Northern Ireland only) gov.uk (England, Wales and Scotland only) or HMRC.
6. Apply For job: Look online at job opportunities or apply for a job online.
7. Leisure: Find information online for your leisure time including cinema and live music.
8. Products: Compare products or services online such as looking at reviews or doing price comparison searches.
9. Cultural activities: Find information online about cultural activities such as museums or theatre.
10. Pay bills: Pay bills or check bills online.
11. Social media: Have at least one social media account.
12. Search engine: Have used a search engine.
13. YouTube: Has watched videos on sites or apps like YouTube, Vimeo, Snapchat or Facebook.
14. Netflix: Has watched TV programmes or films via on-demand or streaming services. such as BBC iPlayer, Netflix, Amazon Prime Video, Sky Go and so on.
15. Gaming: Plays video games on any type of device.
16. Smart phone: Uses a smartphone.
17. New apps sites: Variety of sites and apps used.

Utilising the poLCA package we generated models for two to 10 potential latent classes running 20 iterations for each to avoid local minima. We selected the model with the lowest BIC score (see Table 1) which in this case had six classes (see Figure 1).

NoClasses	ll	df	BIC	AIC	ll_ratio	Chi
2.00	-20884.53	1541.00	42219.17	41891.05	18508.61	36259828.95
3.00	-20084.51	1510.00	40847.89	40353.02	16908.58	34128601.20
4.00	-19746.25	1479.00	40400.12	39738.51	16232.06	13928936.50
5.00	-19536.94	1448.00	40210.24	39381.88	15813.43	17072050.41
6.00	**-19382.32**	**1417.00**	**40129.76**	**39134.64**	**15504.20**	**15057790.79**
7.00	-19288.04	1386.00	40169.95	39008.09	15315.64	17783678.59
8.00	-19206.28	1355.00	40235.17	38906.55	15152.11	12130294.63
9.00	-19137.94	1324.00	40327.25	38831.89	15015.44	13102489.79
10.00	-19073.01	1293.00	40426.13	38764.02	14885.57	12146799.60

Table 1: Latent class analysis - measures of fit

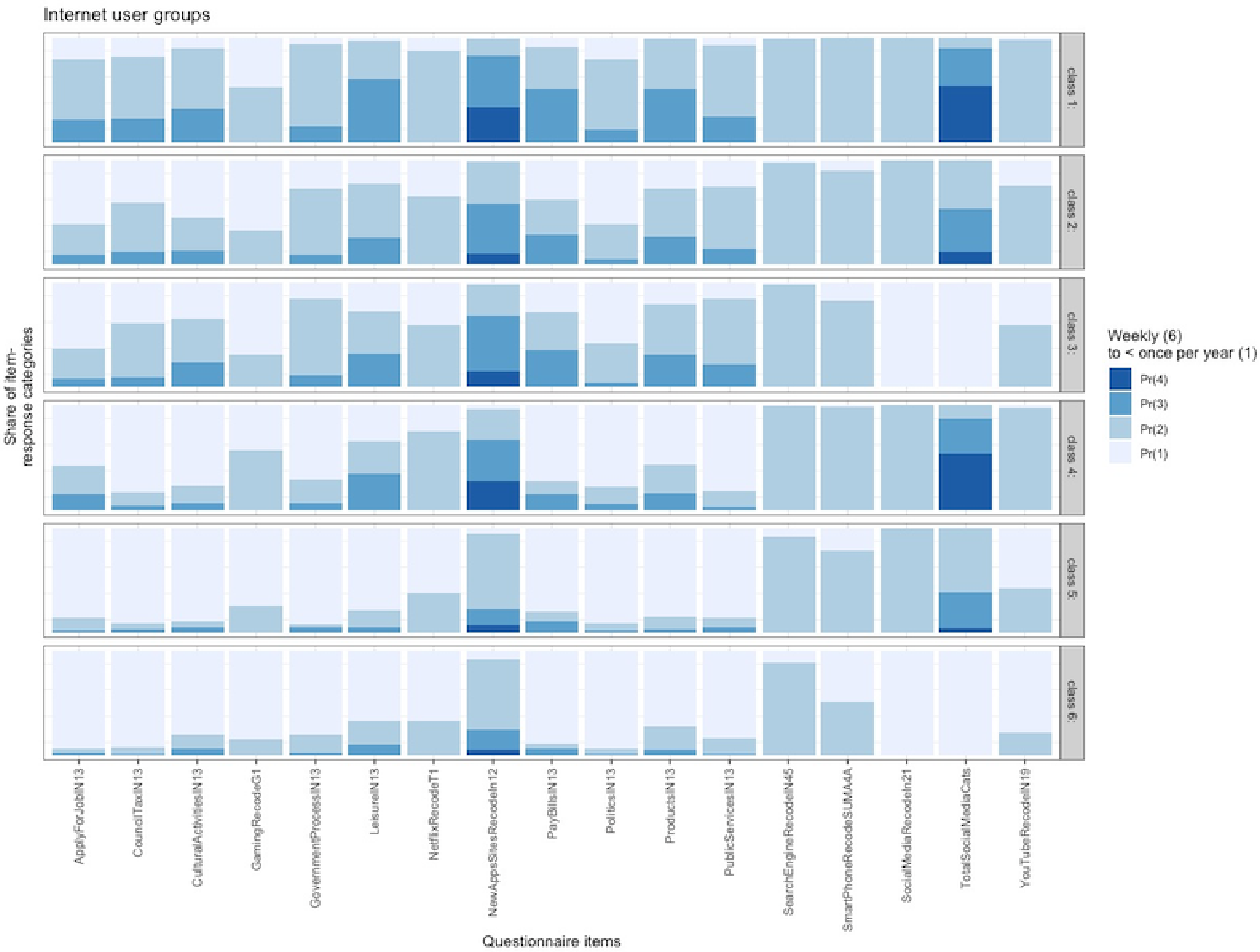


Figure 1: Latent class probability distributions.

Looking at the probability distributions in the six groups we have categorised them as:

- Class 1: "Extensive users" — this group scores the highest probabilities across all behaviours, including a higher than average variety of apps and sites used.

- Class 2: "Non-political extensive users" — this group scores slightly lower across all behaviours as Extensive political users — but notably accepting political uses, including a higher than average variety of apps and sites used.
- Class 3: "General (no social media) users" — this group has a similar behaviour to the Extensive users but does not use social media, including a higher than average variety of apps and sites used.
- Class 4: "Social and entertainment media only users" — this has low usage probabilities (below 50 percent) on all behaviours except social media and audio-visual media consumption, but within this a higher than average variety of apps and sites used.
- Class 5: "Limited (social media) users" — this group has low usage probabilities (below 50 percent) on all behaviours except social media and a lower variety of apps and sites used.
- Class 6: "Limited (no social media) users", this class has low usage probabilities (below 50 percent) on all behaviours and a lower variety of apps and sites used.

We added to this list the group of non-Internet users — that is, people who do not currently have any (non-proxy) access to the Internet giving a total of seven classes. Table 2 compares these groups and their proportions to the results from 2013 and 2016. Some of the variation in the results reflects the change in measures and methods. But we would argue that overall the trend of a growing set of extensive users, a stable 25 percent set of non-political extensive and general users and a persistent 20 percent to 25 percent of limited users.

2013		2015		2018	
Groups	Percent	Groups	Percent	Groups	Percent
Extensive users	4.6	Extensive users	5.2	Extensive users	21.3
Non-political extensive users	11.2	Non-political extensive users	15.4	Non-political extensive users	15.2
General (no social media) users	8.9	General (no social media) users	6.7	General (no social media) users	7.4
Social and entertainement only users	9.7	Social and entertainement media users	14.5	Social and entertainement only users	19.8
Information seeking limited user	12.7	Information seeking limited user	14.6		
Formal transaction users	11.8				
		Limited (social media)	14.4	Limited (social media)	10.0
Limited users	17.2	Limited users	14.3	Limited users	11.5
Non-user	23.8	Non-user	14.9	Non-users	14.9

Table 2: Proportions of user types from prior studies

Our concern in this paper is to explore Classes 4 to 6 — the various forms of limited users of digital services. As noted in the literature review, these groups have access — they are across the first level of the digital divide. We are therefore concerned about how these limited forms of digital media use are in correspondence with other markers of inequality — economic, social and cultural (see Yates and Lockley, 2018). To this end we have undertaken four statistical models

1. Multinomial model of all user types taking extensive users as a base line.
2. Binary logistic model of non-users (Class 7) against users of all types.
3. Binary logistic model of the combined set of limited-users (Class 5 and 6) against other users.
4. Binary logistic model of 'Social and entertainment media only' users (Class 4) as a potential newly identified group.

We have followed this up with specific χ^2 contingency table comparisons of specific variables against group (Class) membership. As we will show below limited and non-user groups have similar characteristics and therefore modelling these against all respondents, rather than the subset of users of all types, does not generate a clear model. In order to assess the demographic characteristics of our user groups (Classes) we operationalised our demographics via the variables outlined in Table 3.

4.2. Comparison across all user types

A more nuanced view of the relationship between our different user types (Classes) was provided by our multinomial regression. A multinomial regression examines likelihood of membership of each group against a baseline group. In this case we took extensive users (Class 1) as the baseline. This is the group most engaged with digital media and the analytical comparisons will therefore show up the demographic differences between this group and those with much lower levels of use. The results of the model are presented in Table 4 and the fit of the model in Table 5 where all variables apart from 'Health impact' are significant contributors.

If we look at the odds ratios for these results, we can make the following claims about each user type (Class) in comparison to the extensive users:

- Non-political extensive users are 2.9 times more likely to be 55+ than under 34, and are between 1.2, 2.4 and 3.6 times more likely to be in NRS social grades [13] C1, C2 and DE respectively. They are more likely (4.0 times) to be retired.

They also have a small likelihood (1.6 times) of being in deprivation and are slightly more likely to have left education at or before age 16 (1.6 times). They are slightly more likely to live in rural than urban areas (1.6 times).

- General (no social media) users are 4.3 times more likely to be 55+ than under 34 but show no significant statistical variance by NRS social grade. They are more likely (5.4 times) to be retired. They also have a small likelihood (1.3 times) of having left education at or before the age of 16.
- 'Social and entertainment media only users' are 3.4 times more likely to be under 34 than over 55+, and are between 1.4, 2.7 and 4.1 times more likely to be in NRS social grades C1, C2 and DE respectively. They also have a higher likelihood (1.4 times) of being in high deprivation. They are 4.5 times more likely to have left education or planning to leave education before the age of 21, though they are the one group more likely to still be in education compared to extensive users (4.9 times).
- Limited (social media) users are 3.5 times more likely to be 55+ than under 34, and are between 1.7, 3.4 and 5.0 times more likely to be in NRS social grades C1, C2 and DE respectively. They are more likely (3.9 times) to be retired. They are 5.9 times more likely to have left education before age of 21. They are more likely to live in rural rather than urban areas (2.4 times).
- Limited (no social media) users have a very similar profile to that of Limited (social media) users. They are 4.9 times more likely to be 55+ than under 34, and are between 1.6, 3.2 and 4.8 times more likely to be in NRS social grades C1, C2 and DE respectively. But they are much more likely (7.5 times) to be retired. They are likely to have left education before age 21 (4.7 times). Though they are not statistically significantly likely to live in more rural than urban areas.
- Non-users are the most distinct from extensive users. They are 10.2 times more likely to be 55+ than under 34, and are between 1.5, 3.1 and 4.7 times more likely to be in NRS social grades C1, C2 and DE respectively. But they are much more likely (8.4 times) to be retired. They have a high likelihood (2.9 times) of being in deprivation and are likely to have left education before age 21 (8.0 times). They are also more likely to live in rented or social housing (2.3 times) and also more likely to be not working (3.4 times).

Variable	Levels	Ofcom variable
Education (age on leaving formal education)	(0) 16 or under; (1) 17-18; (2) 19-20, (3) 21 or over	C7
Health impact (having a condition that affects daily life)	(0) No Impact; (1) Health impact	IN
Household type	From (0) single adult through to (5) multiple adults [3+] with multiple children [3+]	HTYPE
Urban/Rural	(0) Urban; (1) Rural	QLOC
Social Class (NRS Social Grade)	(0) Grades A&B; (1) Grade C1; (2) Grade C2; (3) Grades D&E	AWTV3
Age	(0) 16-34; (1) 35-54; (2) 55+	AWTV2
Deprivation	(1) Low; (1) Medium; (2) High	DEP
Housing owned	(0) Housing owned outright or on mortgage; (1) Housing not owned	C10 (modified)
Working	(0) Not in employment; (1) Currently in employment	C6 (modified)
Retired	(0) Not retired; (1) Retired	C6 (modified)
In formal education	(0) Not in formal education; (1) In formal education	C6 (modified)

Table 3: Key demographic measures

Latent class	(Intercept)	Edu	Health	Household	Urban_Rural	NRS	Age	DEP	Housing	Working	Retired	In Edu
Non-political extensive	-1.43*	-0.25***	0.21	0.02	0.44	0.24*	0.38**	-0.08	-0.34	0.20	1.37***	-0.43
SE	(0.64)	(0.08)	(0.29)	(0.06)	(0.23)	(0.09)	(0.14)	(0.14)	(0.19)	(0.19)	(0.34)	(0.59)
OR	0.24	0.78	1.23	1.02	1.55	1.27	1.46	0.92	0.71	1.22	3.95	0.65
General (no social media)	-2.44**	-0.27**	-0.09	-0.07	0.29	0.09	0.77***	-0.01	-0.13	-0.07	1.69***	0.82
SE	(0.88)	(0.10)	(0.35)	(0.08)	(0.29)	(0.12)	(0.19)	(0.18)	(0.26)	(0.27)	(0.38)	(0.63)
OR	0.09	0.76	0.91	0.94	1.33	1.10	2.15	0.99	0.88	0.93	5.40	2.27
Social and ent. only	-0.19	-0.41***	0.15	0.02	0.40	0.32***	-0.52***	0.34**	-0.01	-0.02	0.72	1.59
SE	(0.62)	(0.07)	(0.30)	(0.05)	(0.24)	(0.09)	(0.13)	(0.13)	(0.18)	(0.18)	(0.42)	(0.33)
OR	0.83	0.66	1.16	1.02	1.49	1.38	0.59	1.41	0.99	0.98	2.06	4.91
Limited (social media)	-3.30***	-0.68***	0.55	0.02	0.88***	0.51***	0.57***	0.30	-0.03	-0.40	1.37***	0.25
SE	(0.81)	(0.10)	(0.30)	(0.07)	(0.26)	(0.11)	(0.17)	(0.17)	(0.23)	(0.24)	(0.36)	(0.68)
OR	0.04	0.51	1.73	1.02	2.40	1.67	1.77	1.35	0.97	0.67	3.95	1.29
Limited (no social media)	-2.91***	-0.45***	0.23	-0.18*	0.16	0.48***	0.88***	0.07	0.15	-0.16	2.02***	-13.18***
SE	(0.83)	(0.09)	(0.30)	(0.08)	(0.27)	(0.11)	(0.19)	(0.17)	(0.24)	(0.25)	(0.35)	(0.00)
OR	0.05	0.64	1.26	0.84	1.17	1.62	2.41	1.07	1.16	0.85	7.52	0.00
Non-users	-3.76***	-0.98***	0.41	-0.23*	0.28	0.47***	1.63***	0.38*	-0.85***	-1.21***	2.12***	-10.15***
SE	(0.96)	(0.11)	(0.29)	(0.09)	(0.29)	(0.11)	(0.23)	(0.18)	(0.24)	(0.32)	(0.35)	(0.00)
OR	0.02	0.38	1.51	0.79	1.32	1.59	5.12	1.46	0.43	0.30	8.36	0.00

[1] *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4: Multinomial regression coefficients

	LR Chisq	Df	Pr(>Chisq)
Education	115.65	6	0.0000
Health impact	6.48	6	0.3720
Household type	14.11	6	0.0284
Urban/Rural	13.74	6	0.0327
NRS social grade	38.23	6	0.0000
Age (short form)	152.74	6	0.0000
Deprivation	17.63	6	0.0072
Housing ownership	24.54	6	0.0004
Working	22.44	6	0.0010
Retired	53.01	6	0.0000
In education	44.56	6	0.0000

Table 5: Fit statistics for multinomial model

4.3. Logistic models of non- and limited users

4.3.1. Non-users (Class 7)

Looking first at non-users, a direct binary logistic regression was performed to assess the impact the factors in Table 3 on the likelihood that respondents would be non-users of the Internet. Non-users being compared to all other users in the full data set. The full model containing all predictors was statistically significant ($\chi^2(11, 1882) = 567.73$, $p = 0.000$) indicating that the model was able to distinguish between non-users and users. The model as a whole explained between 36 percent (McFadden) and 46 percent (Cragg-Uhler) of the variance between non-users and users, and correctly classified 88.5 percent of cases. As shown in Table 6, six of the independent variables made a unique statistically significant contribution to the model:

1. Age (actual or expected) on leaving education — those *not having a post 16 education* (post-high school education) being more likely to be non-users
2. Age — with *older people* (55+) more likely to be non-users
3. Owning your own home outright or by mortgage — *those who do not own their own home* being more likely to be non-users
4. Being in work — those *not in work* more likely to be non-users
5. Retired — those who are *retired* are more likely to be non-users
6. Currently In education — with non-users *very unlikely to be in education*.

From this analysis older citizens who are retirees or not in work, with a more limited education, living in rented accommodation in more highly deprived areas are likely to be non-users of the Internet.

Variable	Non-users	Combibed limited-users	Social and ent. only users
Intercept	-3.92***	-3.07***	-0.29
	(0.82)	(0.56)	(0.53)
Education	-0.62***	-0.33***	-0.19**
	(0.10)	(0.06)	(0.06)
Health impact	0.17	0.38*	-0.15
	(0.18)	(0.18)	(0.23)
Household type	-0.20*	-0.08	0.05
	(0.09)	(0.05)	(0.04)
Urban/Rural	-0.12	0.17	0.10
	(0.22)	(0.18)	(0.20)
NRS social grade	0.12	0.34***	0.12
	(0.09)	(0.07)	(0.08)
Age (short form)	1.37***	0.65***	-0.88***
	(0.20)	(0.12)	(0.11)
Deprivation	0.27	0.13	0.31**
	(0.14)	(0.12)	(0.11)
Housing ownership	-0.82***	0.21	0.07
	(0.19)	(0.16)	(0.15)
Working	-1.16***	-0.30	0.02
	(0.30)	(0.17)	(0.16)
Retired	0.63**	0.73***	-0.77*
	(0.21)	(0.20)	(0.34)
In education	-13.03***	-1.15	1.55***
	(383.35)	(0.61)	(0.27)
N	1882	1602	1602
AIC	1039.35	1466.95	1460.80
BIC	1105.83	1531.50	1525.35
Pseudo R2	0.46	0.30	0.26

[1] All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 6: Non and limited user regression coefficients

4.4. Combination of limited users (Classes 5 and 6)

Looking next at limited users a direct binary logistic regression was performed to assess the impact of the factors in Table 3 on the likelihood that respondents would be either of our two main types of limited users of the Internet (Classes 5 and 6). A subset of data that excluded non-users was employed; limited users were therefore compared to all other types of users but not non-users. The full model containing all predictors was statistically significant ($\chi^2(11, 1882) = 366.42$, $p = 0.000$) indicating that the model was able to distinguish between limited users and all other types of users. The model as a whole explained between 20 percent (McFadden) and 30 percent (Cragg-Uhler) of the variance between limited users and all other types of users and correctly classified 79.4 percent of cases. As shown in Table 6, five of the independent variables made a unique statistically significant contribution to the model:

1. Age (actual or expected) on leaving education — those *not having a post 16 education* being more likely to be limited users
2. Health — those declaring a *health condition that impacts daily life* were more likely to be limited users
3. Social class — those in *social classes C2, D and E* were more likely to be limited users
4. Age — with *older people* more likely to be limited users

5. Retired — those who are *retired* are more likely to be non-users
6. Currently in education — with non-users *very unlikely to be in education*.

From this analysis we could argue that limited users are more likely to be older retired citizens from lower socio-economic groups, who lack a post-16 education and potentially have a chronic health condition.

4.5. Social and entertainment media users only users (Class 4)

A direct binary logistic regression was performed to assess the impact of factors the factors in Table 3 on the likelihood that respondents were 'Social and entertainment media only users' (Class 4). A subset of data that excluded non-users was employed; 'Social and entertainment media only' users were therefore compared to all other types of users but not non-users. The full model containing all predictors was statistically significant ($\chi^2(11, 1882) = 299.55$, $p = 0.000$) indicating that the model was able to distinguish between 'Social and entertainment media only users' and all other types of users. The model as a whole explained between 17 percent (McFadden) and 26 percent (Cragg-Uhler) of the variance between non-users and users, and correctly classified 77.6 percent of cases. As shown in Table 6, five of the independent variables made a unique statistically significant contribution to the model:

1. Age (actual or expected) on leaving education — those *having left education at 16* being more likely to be 'Social and entertainment media only users'
2. Age — with *younger people* more likely to be 'Social and entertainment media only users'
3. Being from an area of higher deprivation — those with *those in the highest levels of deprivation* being more likely to be 'Social and entertainment media only users'
4. Retired — those who are *retired* are very unlikely to be 'Social and entertainment media only users'
5. Currently in education — with 'Social and entertainment media only users' *likely to be in education*.

From this analysis we could argue that 'Social and entertainment media only users' are more most likely to be younger citizens from deprived areas who may have already left education or intend to leave education before 18.

4.6. Key variables and user types (all classes)

The results of the multinomial and individual logistic regression analyses clearly indicate that decreasing levels of digital systems and media use correspond closely with the key variables of education, social class, age and deprivation, with some notable nuances around home ownership, work/retirement and urban/rural location. We therefore undertook chi-square tests for independence between these key variables and user types (Classes) to explore the specific details of each case. The overall results are presented in Table 7. Tables 8 to 15 present the interaction (counts and proportions) between the user types (Classes) and these key variables.

Analysis	chi	df	p	cv	Effect size
Education vs Latent Class	418.25	18	0.00	0.27	Medium
Health impact vs Latent Class	157.50	6	0.00	0.29	Medium
Household type vs Latent Class	425.58	30	0.00	0.21	Medium
Urban/Rural vs Latent Class	15.13	6	0.02	0.09	Small
NRS Social Class vs Latent Class	232.93	18	0.00	0.20	Medium
Age (longform) vs Latent Class	922.10	36	0.00	0.29	Large
Age (short form) vs Latent Class	741.56	12	0.00	0.44	Large
Deprivation vs Latent Class	69.07	12	0.00	0.14	Samll
Housing (longform) vs Latent Class	368.87	24	0.00	0.22	Medium

Table 7: Overall Chi results

As Table 8 details the proportions of user types (Classes) by age on leaving education. Figures 2 through 9 present counts and proportions of cases by age on leaving education and the other key variables of deprivation, age and NRS social grade. These all clearly indicate that leaving education before 16 is a key measure that distinguishes limited and non-users. While having a post 21 education, likely an undergraduate or higher degree, corresponds with our general and extensive users. Our 'Social and entertainment media only users' are in the middle here. As these are mainly young people this likely marks changes in U.K. educational practice where since 2011 the majority of young people now leave secondary (pre-university) education at 18, whereas prior cohorts would have left at 16 or earlier.

Figure 2

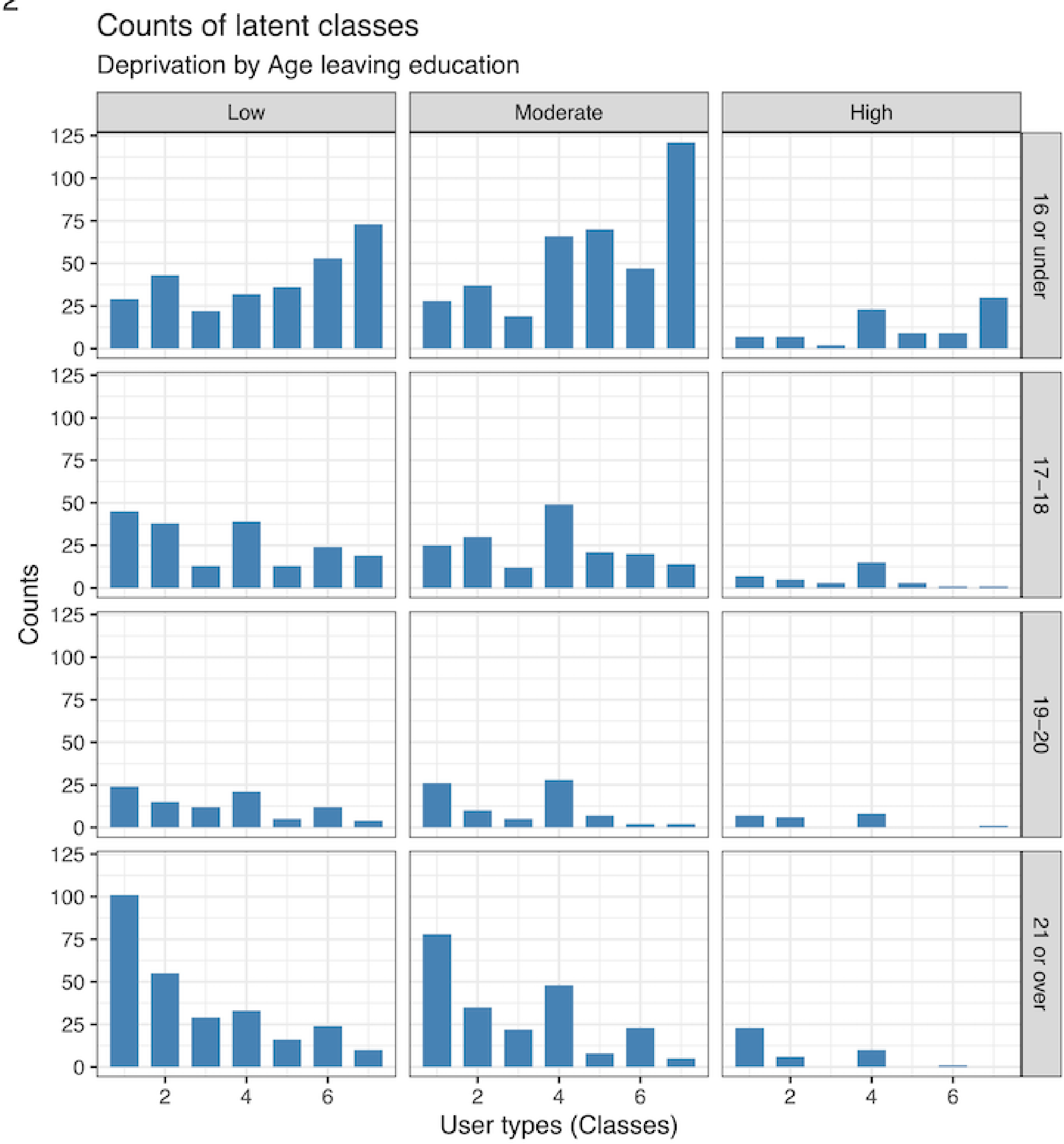


Figure 3


Proportions of latent classes
Deprivation by Age leaving education
Low
Moderate
High
16 or under
17–18
19–20
21 or over
Counts
60.0%
40.0%
20.0%
0.0%
2
4
6
User types (Classes)

Figure 4

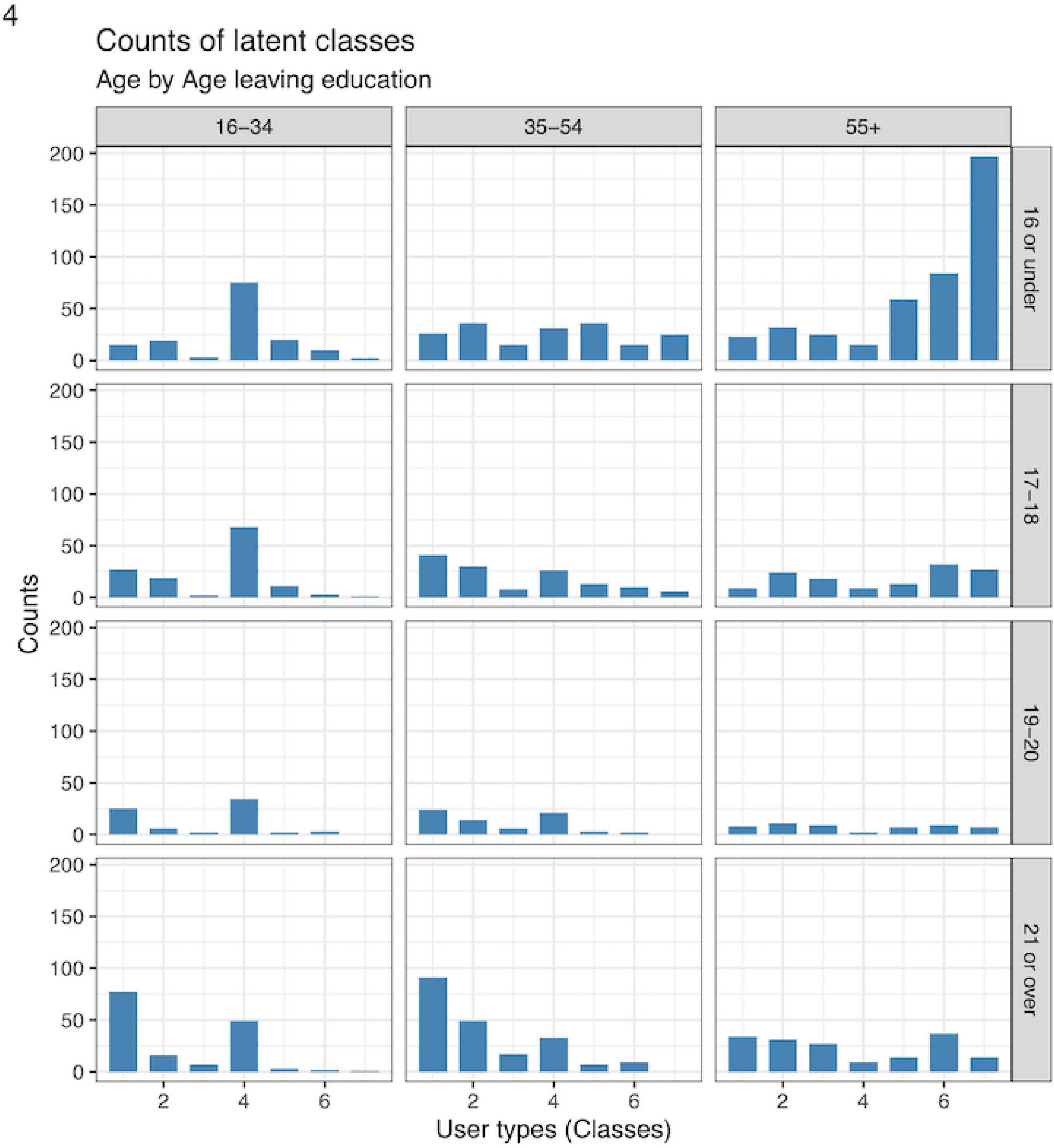

Counts of latent classes
Age by Age leaving education
16–34
35–54
55+
16 or under
17–18
19–20
21 or over
Counts
0
50
100
150
200
2
4
6
User types (Classes)

Figure 5


Proportions of latent classes
Age by Age leaving education
16–34
35–54
55+
16 or under
17–18
19–20
21 or over
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
Counts
2
4
6
User types (Classes)

Latent Class	Aged 16 or under	Aged 17-18	Aged 19-20	Aged 21 or over	Total
Extensive	64	77	57	202	400
row %	16.0	19.2	14.2	50.5	21.3
col %	8.4	19.4	29.2	38.3	
table %	3.4	4.1	3.0	10.7	
Non-political extensive	87	73	31	96	287
row %	30.3	25.4	10.8	33.4	15.2
col %	11.4	18.4	15.9	18.2	
table %	4.6	3.9	1.6	5.1	
General (no social media)	43	28	17	51	139
row %	30.9	20.1	12.2	36.7	7.4
col %	5.6	7.1	8.7	9.7	
table %	2.3	1.5	0.9	2.7	
Social and media	121	103	57	91	372
row %	32.5	27.7	15.3	24.5	19.8
col %	15.9	25.9	29.2	17.3	
table %	6.4	5.5	3.0	4.8	
Social media limited	115	37	12	24	188
row %	61.2	19.7	6.4	12.8	10.0
col %	15.1	9.3	6.2	4.6	
table %	6.1	2.0	0.6	1.3	
Limited	109	45	14	48	216
row %	50.5	20.8	6.5	22.2	11.5
col %	14.3	11.3	7.2	9.1	
table %	5.8	2.4	0.7	2.6	
Non-users	224	34	7	15	280
row %	80.0	12.1	2.5	5.4	14.9
col %	29.4	8.6	3.6	2.8	
table %	11.9	1.8	0.4	0.8	
Total	763	397	195	527	1882
%	40.5	21.1	10.4	28.0	

Table 8: Age on leaving education vs Latent Class

Having a health condition was significant as a predictor for limited users. Though when taken on its own it has a statistically significant interaction with user types (Classes). This has been identified in literature and intervention practice as a key issue that affects daily life but only appeared as a distinguishing factor for our combined limited users' group. Though in Table 9 it is clearly a distinguishing factor for limited users and non-users when viewed alone. Having a health condition that impacts daily life is strongly correlated with other variables especially living in deprived circumstances (χ^2 1, 1882 (Yates' continuity correction)) = 34.094, $p < 0.000$). We would argue that further research is needed to unpick the practical interaction of limiting health conditions (both physical and mental) and use of digital services, especially as ever greater amounts of health care provision includes a digital service element.

Latent Class	No health impact	Health impact	Total
Extensive	375	25	400
row %	93.8	6.2	21.3
col %	24.0	7.8	
table %	19.9	1.3	
Non-political extensive	249	38	287
row %	86.8	13.2	15.2
col %	16.0	11.8	
table %	13.2	2.0	
General (no social media)	121	18	139
row %	87.1	12.9	7.4
col %	7.8	5.6	
table %	6.4	1.0	
Social and media	338	34	372
row %	90.9	9.1	19.8
col %	21.7	10.6	
table %	18.0	1.8	
Social media limited	138	50	188
row %	73.4	26.6	10.0
col %	8.8	15.6	
table %	7.3	2.7	
Limited	166	50	216
row %	76.9	23.1	11.5
col %	10.6	15.6	
table %	8.8	2.7	
Non-users	174	106	280
row %	62.1	37.9	14.9
col %	11.1	33.0	
table %	9.2	5.6	
Total	1561	321	1882
%	82.9	17.1	

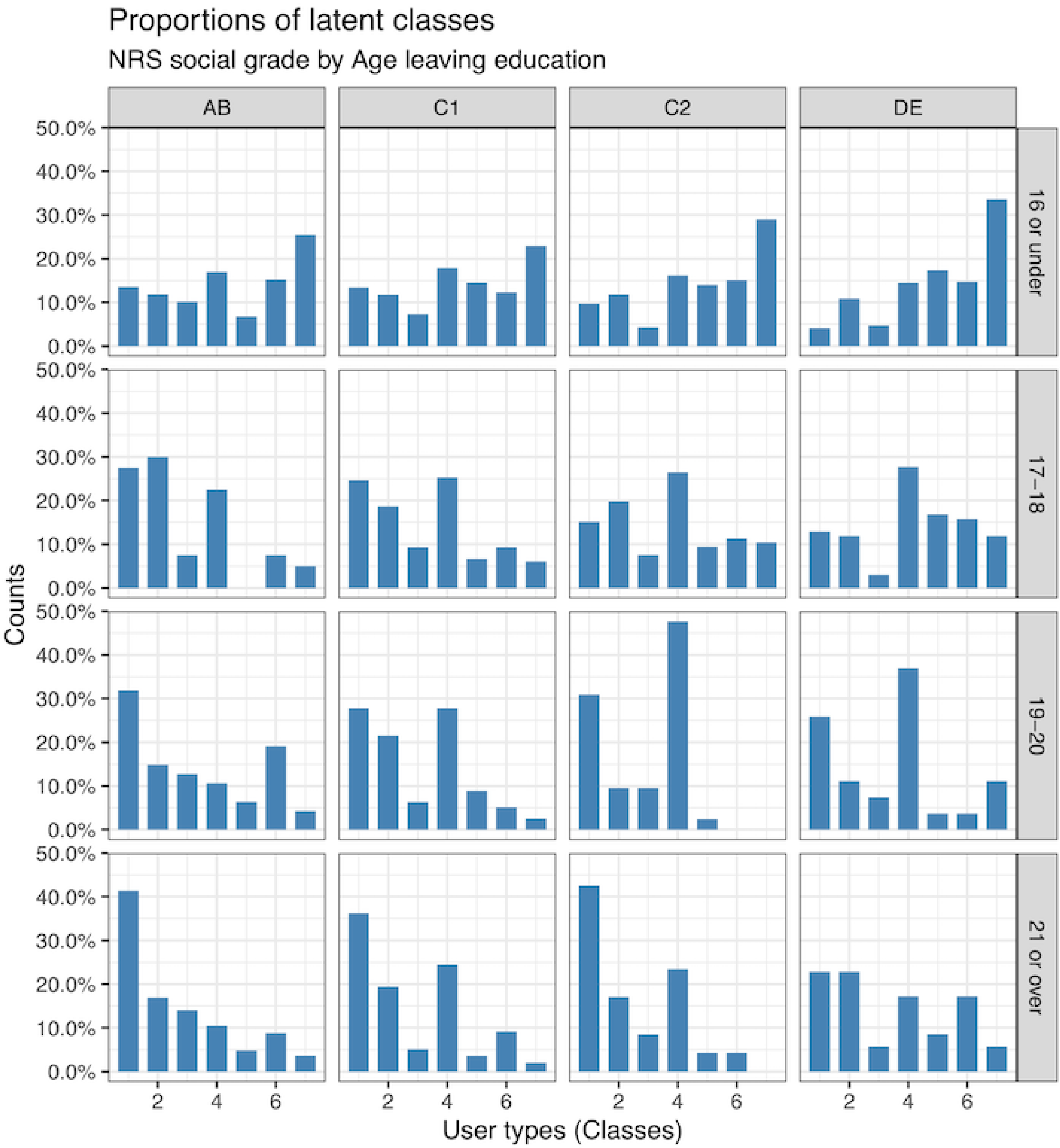
Table 9: Health impact vs Latent Class

We have noted elsewhere (Yates, *et al*, 2015; Yates and Lockley, 2018) that social class, viewed through a standard measure such as NRS social grade, or via more complex measures of different forms of capital has a strong correspondence with levels and types of digital media use. This is clearly the case here as well (see Table 10 and Figures 2, 3 and 6 to 9). Limited and non-users being far more likely to be in social grades D and E and our more engaged groups in social grades A and B. Similarly, our social and entertainment media users group as well as the limited user types and non-users are all more likely to be in households with higher levels of deprivation.

Figure 6


Counts of latent classes
NRS social grade by Age leaving education
AB
C1
C2
DE
16 or under
17–18
19–20
21 or over
Counts
90
60
30
0
2
4
6
User types (Classes)

Figure 7



Proportions of latent classes
NRS social grade by Age leaving education
AB
C1
C2
DE
16 or under
17–18
19–20
21 or over
Counts
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
2
4
6
User types (Classes)

Figure 8

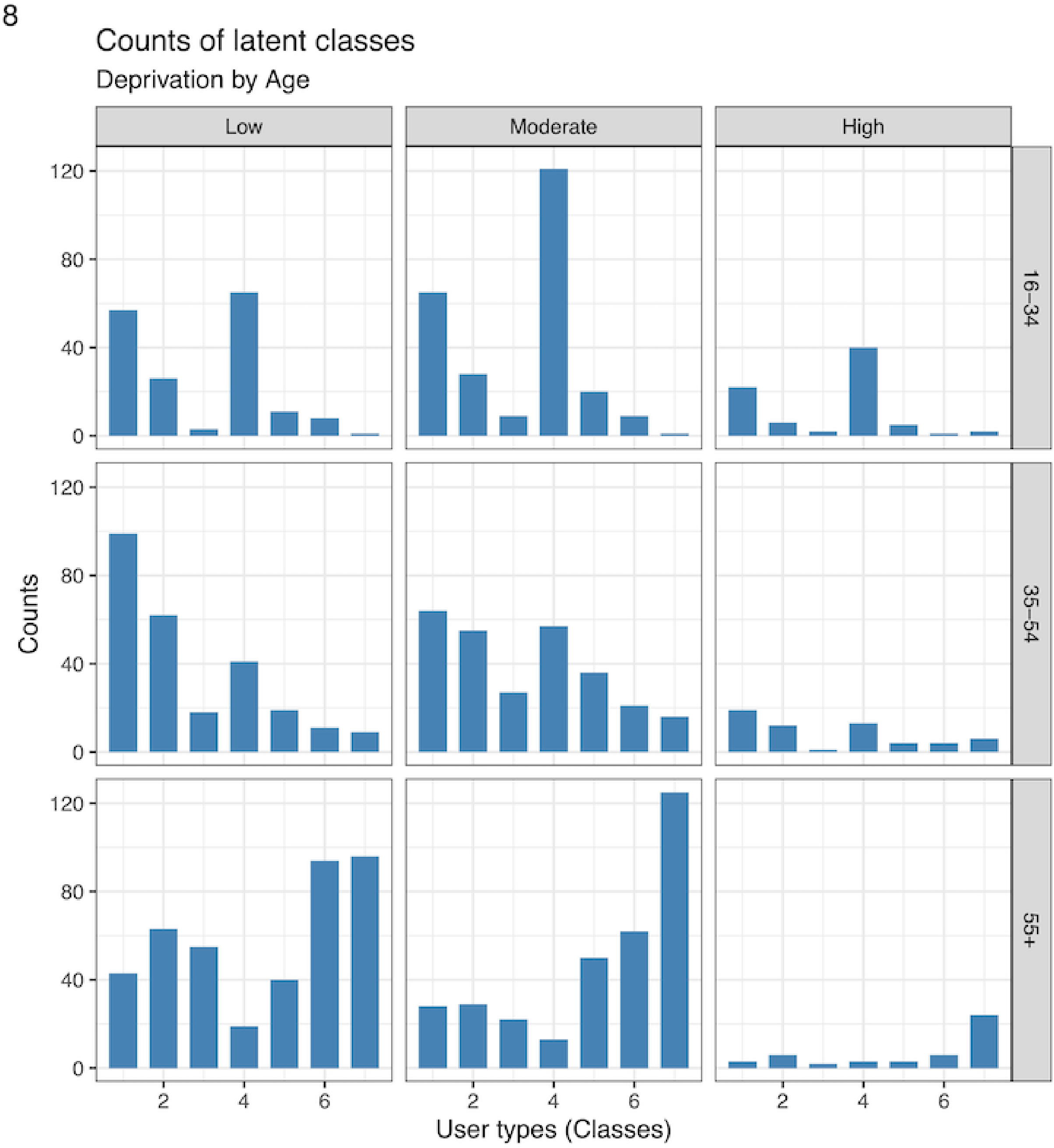
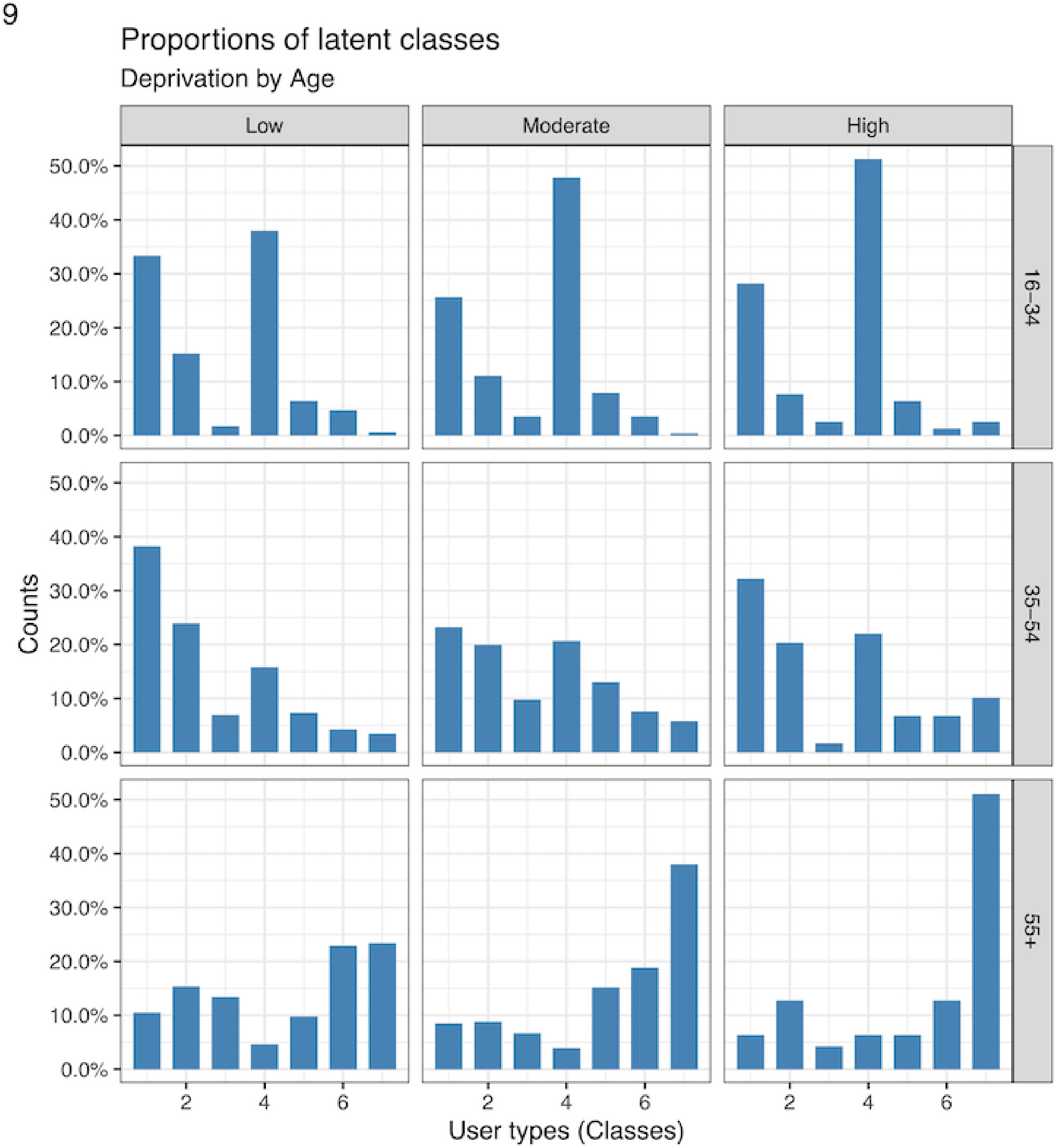

Counts of latent classes
Deprivation by Age
Low
Moderate
High
16–34
35–54
55+
Counts
User types (Classes)
0
40
80
120
2
4
6

Figure 9


Proportions of latent classes
Deprivation by Age
Low
Moderate
High
16–34
35–54
55+
Counts
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
2
4
6
User types (Classes)

Latent Class	AB	C1	C2	DE	Total
Extensive political	137	154	67	42	400
row %	34.2	38.5	16.8	10.5	21.3
col %	34.7	25.5	17.6	8.4	
table %	7.3	8.2	3.6	2.2	
Extensive	68	104	55	60	287
row %	23.7	36.2	19.2	20.9	15.2
col %	17.2	17.2	14.4	12.0	
table %	3.6	5.5	2.9	3.2	
General (no social media)	50	42	24	23	139
row %	36.0	30.2	17.3	16.5	7.4
col %	12.7	7.0	6.3	4.6	
table %	2.7	2.2	1.3	1.2	
Social and media	50	140	89	93	372
row %	13.4	37.6	23.9	25.0	19.8
col %	12.7	23.2	23.4	18.5	
table %	2.7	7.4	4.7	4.9	
Social media limited	19	50	39	80	188
row %	10.1	26.6	20.7	42.6	10.0
col %	4.8	8.3	10.2	15.9	
table %	1.0	2.7	2.1	4.3	
Limited	43	58	42	73	216
row %	19.9	26.9	19.4	33.8	11.5
col %	10.9	9.6	11.0	14.5	
table %	2.3	3.1	2.2	3.9	
Non-users	28	56	65	131	280
row %	10.0	20.0	23.2	46.8	14.9
col %	7.1	9.3	17.1	26.1	
table %	1.5	3.0	3.5	7.0	
Total	395	604	381	502	1882
%	21.0	32.1	20.2	26.7	

Table 10: NRS social grade vs Latent Class

Latent Class	Urban	Rural	Total
Extensive political	349	51	400
row %	87.2	12.8	21.3
col %	22.1	16.7	
table %	18.5	2.7	
Extensive	232	55	287
row %	80.8	19.2	15.2
col %	14.7	18.0	
table %	12.3	2.9	
General (no social media)	113	26	139
row %	81.3	18.7	7.4
col %	7.2	8.5	
table %	6.0	1.4	
Social and media	320	52	372
row %	86.0	14.0	19.8
col %	20.3	17.0	
table %	17.0	2.8	
Social media limited	144	44	188
row %	76.6	23.4	10.0
col %	9.1	14.4	
table %	7.7	2.3	
Limited	179	37	216
row %	82.9	17.1	11.5
col %	11.4	12.1	
table %	9.5	2.0	
Non-users	239	41	280
row %	85.4	14.6	14.9
col %	15.2	13.4	
table %	12.7	2.2	
Total	1576	306	1882
%	83.7	16.3	

Table 11: QLOC vs Latent Class

As indicated in our regression model, Limited (social media) users (Class 5) are likely to be rural. Table 11 presents the proportions of our latent class groups who are urban and rural. In all of the literature and policy work age remains a key issue. This is clearly the case in our analyses too. Tables 12 and 13 take a more detailed look at age and we find a clear pattern. Both of our limited user categories and non-users are more likely to be over 55, with non-users far more likely to be over 65. Extensive users are more likely to be of working age. Social and entertainment media users are predominantly under 24. Leaving our General and Limited (social media) users' categories less defined statistically by age.

Latent Class	16-24	25-34	35-44	45-54	55-64	65-74	75+	Total
Extensive political	51	93	105	77	56	14	4	400
row %	12.8	23.2	26.2	19.2	14.0	3.5	1.0	21.3
col %	20.7	36.3	32.6	28.3	18.1	6.3	1.6	
table %	2.7	4.9	5.6	4.1	3.0	0.7	0.2	
Extensive	24	36	61	68	53	30	15	287
row %	8.4	12.5	21.3	23.7	18.5	10.5	5.2	15.2
col %	9.8	14.1	18.9	25.0	17.2	13.6	5.9	
table %	1.3	1.9	3.2	3.6	2.8	1.6	0.8	
General (no social media)	6	8	24	22	30	27	22	139
row %	4.3	5.8	17.3	15.8	21.6	19.4	15.8	7.4
col %	2.4	3.1	7.5	8.1	9.7	12.2	8.6	
table %	0.3	0.4	1.3	1.2	1.6	1.4	1.2	
Social and media	141	85	72	39	24	5	6	372
row %	37.9	22.8	19.4	10.5	6.5	1.3	1.6	19.8
col %	57.3	33.2	22.4	14.3	7.8	2.3	2.3	
table %	7.5	4.5	3.8	2.1	1.3	0.3	0.3	
Social media limited	14	22	31	28	37	29	27	188
row %	7.4	11.7	16.5	14.9	19.7	15.4	14.4	10.0
col %	5.7	8.6	9.6	10.3	12.0	13.1	10.5	
table %	0.7	1.2	1.6	1.5	2.0	1.5	1.4	
Limited	7	11	16	20	51	46	65	216
row %	3.2	5.1	7.4	9.3	23.6	21.3	30.1	11.5
col %	2.8	4.3	5.0	7.4	16.5	20.8	25.4	
table %	0.4	0.6	0.9	1.1	2.7	2.4	3.5	
Non-users	3	1	13	18	58	70	117	280
row %	1.1	0.4	4.6	6.4	20.7	25.0	41.8	14.9
col %	1.2	0.4	4.0	6.6	18.8	31.7	45.7	
table %	0.2	0.1	0.7	1.0	3.1	3.7	6.2	
Total	246	256	322	272	309	221	256	1882
%	13.1	13.6	17.1	14.5	16.4	11.7	13.6	

Table 12: Age (Long form) vs Latent Class

Latent Class	16-34	35-54	55+	Total
Extensive political	144	182	74	400
row %	36.0	45.5	18.5	21.3
col %	28.7	30.6	9.4	
table %	7.7	9.7	3.9	
Extensive	60	129	98	287
row %	20.9	44.9	34.1	15.2
col %	12.0	21.7	12.5	
table %	3.2	6.9	5.2	
General (no social media)	14	46	79	139
row %	10.1	33.1	56.8	7.4
col %	2.8	7.7	10.1	
table %	0.7	2.4	4.2	
Social and media	226	111	35	372
row %	60.8	29.8	9.4	19.8
col %	45.0	18.7	4.5	
table %	12.0	5.9	1.9	
Social media limited	36	59	93	188
row %	19.1	31.4	49.5	10.0
col %	7.2	9.9	11.8	
table %	1.9	3.1	4.9	
Limited	18	36	162	216
row %	8.3	16.7	75.0	11.5
col %	3.6	6.1	20.6	
table %	1.0	1.9	8.6	
Non-users	4	31	245	280
row %	1.4	11.1	87.5	14.9
col %	0.8	5.2	31.2	
table %	0.2	1.6	13.0	
Total	502	594	786	1882
%	26.7	31.6	41.8	

Table 13: Age (Short form) vs Latent Class

Latent Class	Low	Medium	High	Total
Extensive	199	157	44	400
row %	49.8	39.2	11.0	21.3
col %	23.7	18.3	23.9	
table %	10.6	8.3	2.3	
Non-political extensive	151	112	24	287
row %	52.6	39.0	8.4	15.2
col %	18.0	13.1	13.0	
table %	8.0	6.0	1.3	
General (no social media)	76	58	5	139
row %	54.7	41.7	3.6	7.4
col %	9.0	6.8	2.7	
table %	4.0	3.1	0.3	
Social and media	125	191	56	372
row %	33.6	51.3	15.1	19.8
col %	14.9	22.3	30.4	
table %	6.6	10.1	3.0	
Social media limited	70	106	12	188
row %	37.2	56.4	6.4	10.0
col %	8.3	12.4	6.5	
Limited	113	92	11	216
row %	52.3	42.6	5.1	11.5
col %	13.5	10.7	6.0	
table %	6.0	4.9	0.6	
Non-users	106	142	32	280
row %	37.9	50.7	11.4	14.9
col %	12.6	16.6	17.4	
table %	5.6	7.5	1.7	
Total	840	858	184	1882
%	44.6	45.6	9.8	

Table 14: Deprivation vs Latent Class

4.7. Smart and mobile device use

As a last analysis we have examined the link between user types (Classes) and the devices members use. We split respondents into those who used a variety of devices, including a laptop or desktop PC, and those who only used smart or mobile devices such as tablets and smartphones. We find a strong link between user types and the devices they use ((χ^2(5, 1602 (Yates' continuity correction)) = 150.118, p < 0.000). Table 15 provides a breakdown of the proportions between device use and user types (Classes). Figures 10 to 13 explore this in terms of the key variables of education and NRS social grade. As with the findings above there is a clear pattern of wealthier, more educated and extensive users having access to more substantive ICT equipment. In contrast poorer, less educated citizens being more likely to only use smart or mobile devices. The very distinct group here are our 'Social and entertainment media only users' group (Class 4). As noted above they are younger people with lower educational attainment, from lower NRS social grade and more highly deprived homes. They are also the group most likely to only use smart or mobile devices.

Figure 10

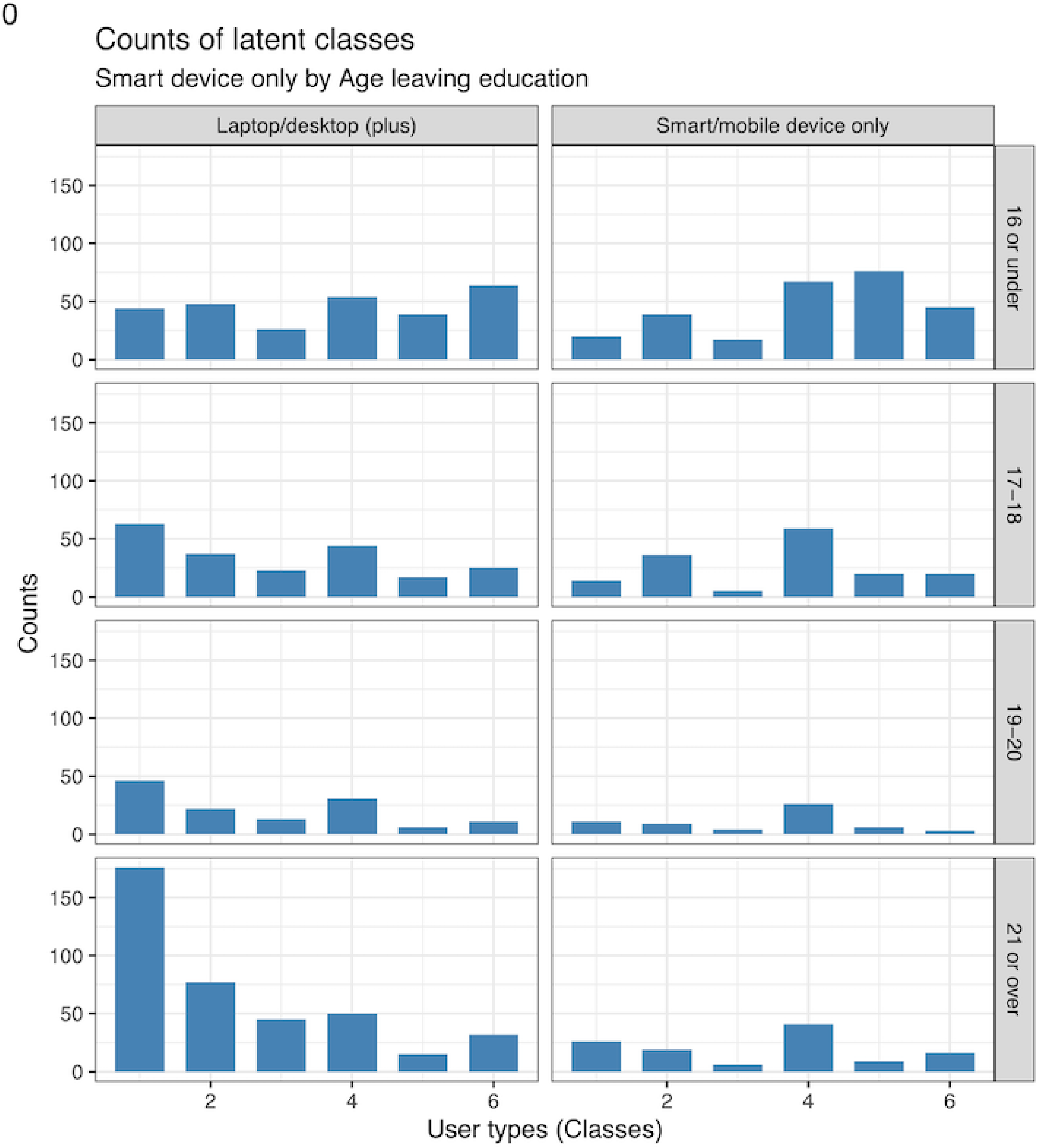


Figure 11

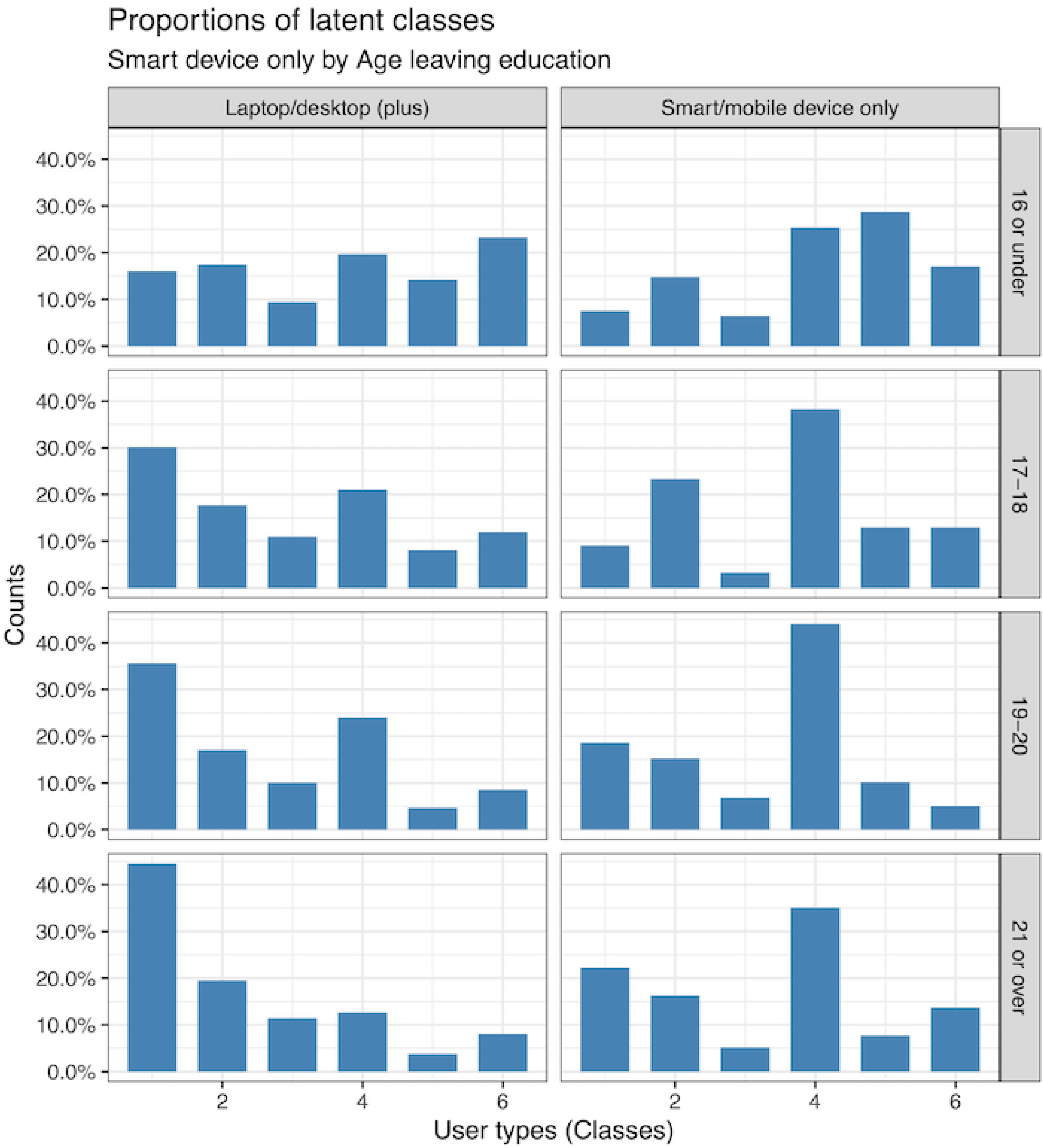

Proportions of latent classes
Smart device only by Age leaving education
Laptop/desktop (plus)
Smart/mobile device only
16 or under
17–18
19–20
21 or over
Counts
40.0%
30.0%
20.0%
10.0%
0.0%
2
4
6
User types (Classes)

Figure 12

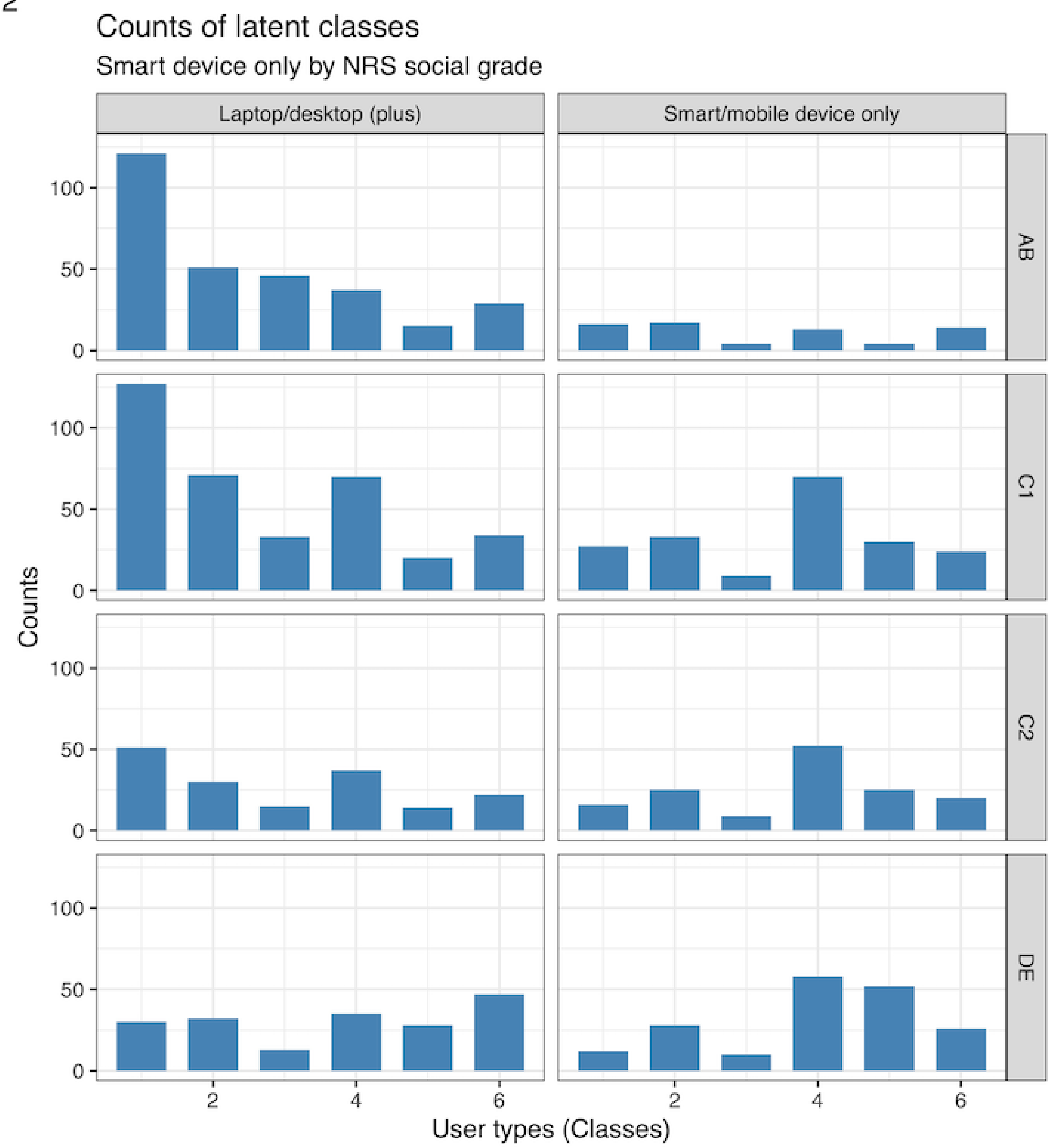
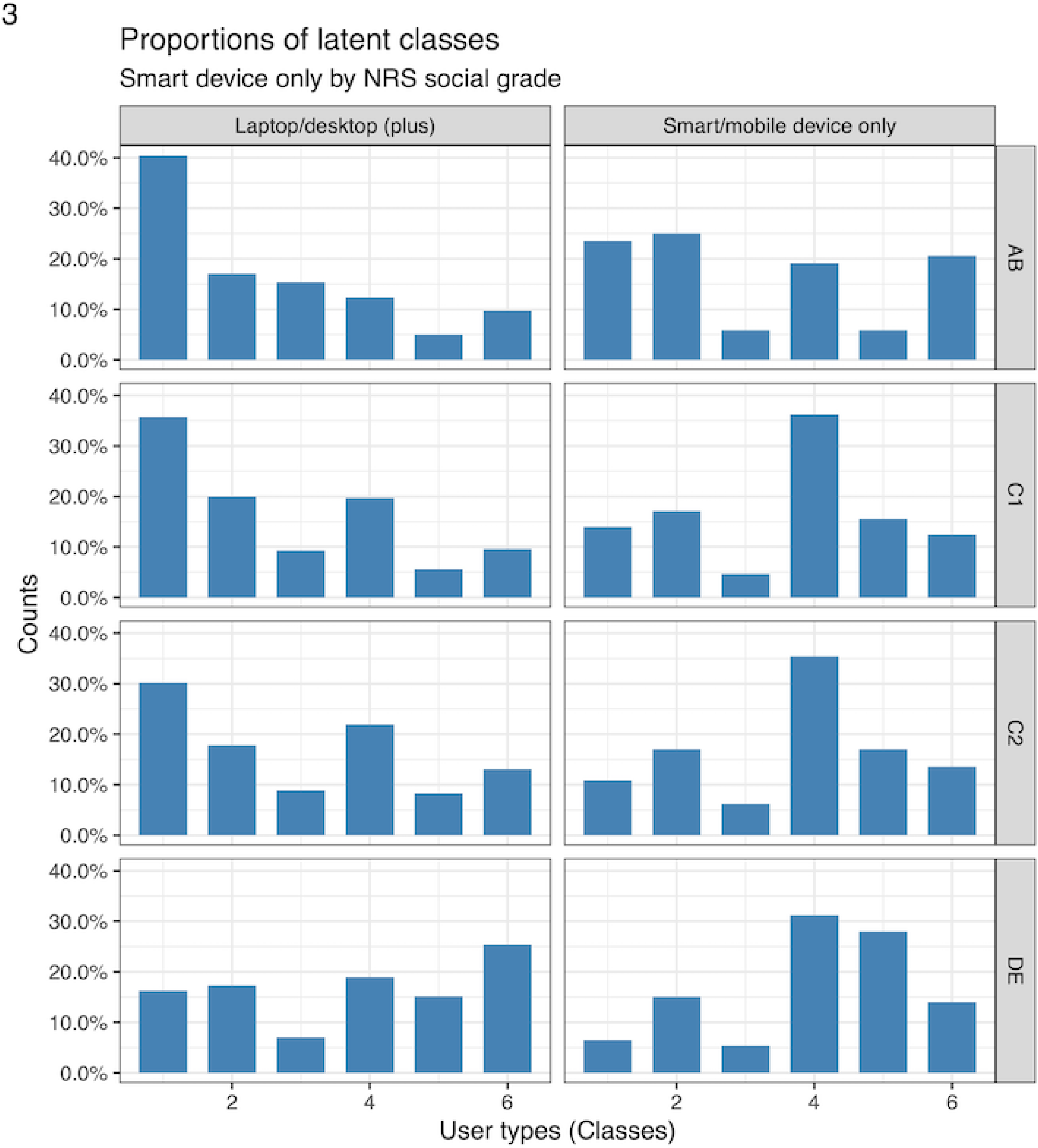

Counts of latent classes
Smart device only by NRS social grade
Laptop/desktop (plus)
Smart/mobile device only
AB
C1
C2
DE
Counts
0
50
100
2
4
6
User types (Classes)

Figure 13


Proportions of latent classes
Smart device only by NRS social grade
Laptop/desktop (plus)
Smart/mobile device only
AB
C1
C2
DE
Counts
40.0%
30.0%
20.0%
10.0%
0.0%
2
4
6
User types (Classes)

Latent Class	Laptop/PC or Multi-device user	Phone or tablet only	Total
Extensive	329	71	400
row %	82.2	17.8	25.0
col %	32.6	12.0	
table %	20.5	4.4	
Non-political extensive	184	103	287
row %	64.1	35.9	17.9
col %	18.3	17.3	
table %	11.5	6.4	
General (no social media)	107	32	139
row %	77.0	23.0	8.7
col %	10.6	5.4	
table %	6.7	2.0	
Social and media	179	193	372
row %	48.1	51.9	23.2
col %	17.8	32.5	
table %	11.2	12.0	
Social media limited	77	111	188
row %	41.0	59.0	11.7
col %	7.6	18.7	
table %	4.8	6.9	
Limited	132	84	216
row %	61.1	38.9	13.5
col %	13.1	14.1	
table %	8.2	5.2	
Total	1008	594	1602
%	62.9	37.1	

Table 15: Smart Device Only vs Limited Users

5. Discussion

Taking our results together we would argue that our inductively derived user types (Classes) and their clear social and demographic variation provides a strong basis for exploring and examining the varied social, cultural and economic contexts of citizens' digital systems and media use in the U.K. Though gaining access and skills are key to any use of digital systems and media — our findings show that the context in which access is acquired or skills used is central to the levels and types of use. Taking the first three groups (Classes 1 to 3) of more active users. *Extensive users* (who are likely to be employed, under 55 from middle to higher socio-economic grade and to have a post 16, very likely post 21 education) are likely to have a very rich and diverse access as well as diverse digital skills. Similarly, *non-political extensive users* (who are likely to be older [55+] and of middle socio-economic grade and in employment) are again likely to have both richer access and skills than most other citizens. *General (non-social media) users* (older [55+] retired citizens not in poverty) are again likely to have a more favourable social context.

In terms of our three groups (Classes 4 to 6) of limited users we noted some clear distinctions around social context. *Social and entertainment media users only users* (likely to be under 34, from social class DE and in higher deprivation) are comparable to similar groups identified in more qualitative literature (Scheerder, *et al.*, 2019; Fernandez, *et al.*, 2019; Robinson, 2011, 2009). Their demographic profile could mark them out as 'precarious young poor' (Standing, 2014a; 2014b). Importantly, their limited and narrow use is not simply defined by a lack of material access nor basic digital skills but appears to reflect their broader social context. There are clear overlaps between our two groups (Classes 5 and 6) who are very limited users but also some key differences. *Limited (social media) users* are more likely to have health issues, to be 55+, to be in social class DE, to have left school at 16 than have higher qualifications, and are almost entirely rural. We might interpret this group as older rural poor. We might speculate that their engagement with social media reflects their rural context and the need to stay in contact with family and friends. The *Limited (no social media) users'* group are more likely to have health issues, have left school at 16 than have a degree, to be in social class DE and to be 55+. We might interpret this group as being older poor — urban or rural. *Non-users* remain the most distinct group and have the most constrained and limited social context; being more likely to be older (55+), be in social housing, to be in higher deprivation, to have health issues, to be in social class DE and to have left school at 16.

We might speculate that we could see two 'life course' trajectories in these seven groups. In the first, extensive users mark the early life of those who post-retirement become our general users. Similarly, narrow Social and entertainment media users might over time become our limited users or non-users. Such a picture would be overly simplistic. We would argue that our age and education variables also encompass how and where citizens will have engaged with digital systems and media as they have developed over the last four decades. Older citizens will have encountered such developments later in life and may or may not have engaged with technologies in the workplace or education. Younger citizens, especially those in our 'Extensive user' and 'Social and entertainment media only users' groups (Classes) represent groups who have grown up after and alongside the major Internet, digital and mobile media innovations. As a result, different groups of citizens have integrated digital systems and media into their lives, heavily influenced by their social, economic and cultural capital.

We are not arguing here that the pattern of user groups (Classes) is simply the product of cohort effects, far from it. Rather we are arguing that these groups reflect a complex interplay of contexts, both social and digital, and that there is no simple linear link from access, via skills to user types or outcomes. We are concerned that our younger Social and entertainment media only users' group has the potential to develop into an older cohort with limited and narrow digital skills that will exclude them from access to broader social, civic, economic and personal opportunities. We would argue that further work is needed to understand the detailed social context of these user groups (Classes), the tangible social consequences for citizens in these groups and the longer-term impacts of membership of groups earlier in the life course.

5.1. Policy relevance

Our analysis and findings, especially the set of user types provides a tool for policy-makers and NGO practitioners to develop policies, strategies and education activities which attend to these groups' life courses more holistically. Often policy-makers focus on targets such as access (via improving broadband availability) or skills (via educational initiatives or third sector training support) as they are easily identified and quantified. The results here indicate that the underlying variables behind limited use of digital systems and media are the more intractable and challenging issues around social inequality, potentially deprivation and exit from formal education. The key message for policy-makers is to more fully consider the local and personal social contexts of citizens when designing interventions, what we call 'networks of literacy'. This means understanding people's communities and how to tailor intervention strategies in a way that is meaningful to them and their everyday lives.

The appropriate interventions for the social and entertainment media user group (Class 4) are likely to be very different from those that will target rural limited users or non-users. Therefore, there is no one intervention or education programme that is a one-size-fits all, and more tailoring to the specific social, economic and cultural conditions of each group needs to be addressed. The results, along with many others noted here (Yates, *et al.*, 2015; Yates and Lockley, 2018; Helsper, *et al.*, 2015; Robinson, 2011, 2009; Fernandez, *et al.*, 2019) also argue for careful consideration of how, when and if services that support more marginalised groups and individuals can and should be delivered digitally or are there approaches that can cater the in-between.

People's 'networks of literacy' can be acquired in many ways and places with families, peers, co-workers, libraries, communities and so on. Further work on the motivations and goals of citizens around digital systems and media use within these user groups may also help policy-makers identify more effective routes to engage citizens with digital. Finally, further work is needed to understand if these different user types (Classes) are at greater or less risk of digital harms (United Kingdom. Department for Digital, Culture, Media and Sport (DCMS), 2020), impacts of digitisation and automation of work, or alternatively if they disproportionately gain benefits from digital engagement.

6. Conclusion

In this paper we unpicked what it means to be a limited user in the context of the U.K., by using Ofcom's 2019 survey data. While there is academic work on different types of digital media and systems uses, including those who do not use them at all (called non-users), we know very little about the 'limited users' group. As has been pointed out in a range of more qualitative studies (Fernandez, *et al.*, 2019; Robinson, 2011, 2009) the key issue for many citizens is not simply one of access, nor can a lack of engagement with digital systems and media be explained solely by as lack of skills. Taking these qualitative findings to a national survey scale we have found that limited use significantly corresponds most with a range of factors that act in combination. First, the likelihood of lacking a post 16 education. This result mirrors Scheerder, *et al.* (2019). It points to a clear correspondence between a potential lack of digital engagement and digital skills with broader limited cultural capital.

Second, the likelihood of being from a higher deprivation context. This replicates many of the prior studies noted in this paper where low levels of income are often associated with problematic, limited or intermittent access, and the need to find creative "workaround activities" (Rhinesmith, *et al.*, 2019). Third, the likelihood of being in a lower socio-economic status group. As we have documented elsewhere, social class remains a key predictor of the levels and types of digital systems and media use (Yates and Lockley, 2018). The NRS social grade scale used in the analyses here, as it is based on existing or prior (pre-retirement) employment, acts as a proxy for a combination of factors that overlap including employment status as well as income and therefore implicitly likely levels of education/training. Given the growth of digital based employment, further work may be needed to unpick the extent to which levels of digital systems used in the workplace impact overall engagement.

The fourth factor appears to be life stage — especially being older (in particular post retirement), or younger (under 34) but only in combination with other factors. In all data over the last two decades, older people have consistently been most likely to be off-line or limited users of digital systems and media. The key question has been whether this is a cohort effect, which will fade over time as younger users age, or an effect of life stage. The evidence here and elsewhere (Blank and Dutton, 2019) of the persistent decline in levels of digital use as citizens age greatly strengthens the case that there is strong life stage and context factor at work combining age, education, deprivation and social class.

At the same time, there is growing evidence of limited or "narrow use" (Ofcom, 2019) among younger citizens. Especially where use is limited to social media and audio-visual media. Again, this might indicate a life stage effect arising for the availability of smart devices — younger people using these to focus on activities that they prioritise. Yet the strong correspondence with deprivation and education as well as the presence of similarly aged higher socio-economic status citizens in the extensive user group (Class 1) would indicate that younger citizens social context is important here as well. The key question will be whether this group will continue as narrow or limited users throughout their life course. In the context of habitus as highlighted in prior studies (Scheerder, *et al.*, 2019; Yates and Lockley, 2020b; Robinson, 2011, 2009) there is question as to how this experience of digital at a younger age will impact the overall set of skills and attitudes to digital that will be taken into later life. These factors combine to produce clear and distinct variations between our seven user types (Classes). To conclude — context matters, and the way governments and the third sector should approach these different groups of citizens is through ways that cater to these differences to have long-term and meaningful impact on their lives.

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Acknowledgements

This research was made possible by support from Good Things Foundation and the Nuffield Foundation. This work was conducted as part of a collaboration with Good Things Foundation to provide evidence in support of their "100% digital included U.K." goals. Further, analyses were supported as part of the Nuffield Foundation funded project "Me and my big data — developing citizens' data literacies".

Notes

1. https://www.ofcom.org.uk/research-and-data/media-literacy-research.

2. https://www.pewresearch.org/internet/.

3. For example the DCMS Essential Digital Skills Framework: https://www.gov.uk/government/publications/essential-digital-skills-framework/essential-digital-skills-framework.

4. Jaeger, *et al.*, 2012, p. 3.

5. Hargittai, 2001, p. 3.

6. van Dijck and Hacker, 2003, p. 325.

7. Helsper, *et al.*, 2015, p. 12.

8. Blank and Dutton, 2019, p. 5.

9. Scheerder, *et al.*, 2019, p. 2,114.

10. Rhinesmith, *et al.*, 2019, p. 122.

11. Fernandez, *et al.*, 2019, p. 8.

12. Fernandez, *et al.*, 2019, p. 16.

13. 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.

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Editorial history

Received 6 June 2020; accepted 9 June 2020.

Who are the limited users of digital systems and media? An examination of U.K. evidence
by Simeon J. Yates, Elinor Carmi, Eleanor Lockley, Alicja Pawluczuk, Tom French, and Stephanie Vincent.
First Monday, Volume 25, Number 7 - 6 July 2020
https://firstmonday.org/ojs/index.php/fm/article/download/10847/9565
doi: http://dx.doi.org/10.5210/fm.v25i7.10847