Moving on up in the Information Society? A longitudinal analysis of the relationship between Internet use and social class mobility in Britain

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Abstract

Many universal access policies are based on the assumption that the removal of the digital divide will enhance social mobility. But this assumption is not supported by the available evidence and hence remains an open question. Using four waves of longitudinal data from Britain we show that Internet use has a positive effect on social class mobility, while controlling for age, gender, education, health, and previous social class membership between 1997 and 2013. In doing so, we contribute to a wider discussion of the relationships between social and digital inequalities and highlight the challenges and potential of this methodological approach for future research.

Keywords: social mobility, Internet use, social class, digital inequalities, digital inclusion, digital divide, reciprocal effects

Moving on up in the Information Society?

A longitudinal analysis of the relationship between Internet use and social class mobility in Britain

Since the last decade of the twentieth century policymakers have sought to close the digital divide so that everyone can use the Internet and other digital technologies in a meaningful and effective way to fully participate in the information society. This policy focus on getting people "online" is based on an assumption that Internet use is positively related to a wide range of social, economic and psychological outcomes, and is critical for individuals to gain access to a wide range of opportunities that may improve social mobility and life circumstances. However, this assumption is not supported by the available evidence and hence remains an open question.

Scholars have critiqued the deterministic and simplistic claims that underpin such discourse (Chen and Wellman 2005; Gunkel 2003; Eubanks 2011; Stevenson 2009) and have instead theorised the links between digital and social inequality as multi-directional with social and digital inequalities influencing one another (DiMaggio et al. 2004; Helsper 2012; van Dijk, 2005; Selwyn 2004). However, there is little quantitative evidence to support this consequential claim. There is a great deal of research that highlights how existing social inequalities influence the adoption and use of technology (Reisdorf and Grosel 2017; van Deursen and van Dijk 2015; Zillien and Hargittai 2009). However, there is far less evidence, particularly from a quantitative perspective that shows how Internet use influences social stratification and life chances Hargittai and Hsieh, 2013).

Models that explore the relationships between digital and social inequalities have grown increasingly sophisticated over the past few decades. They have moved away from a simple dichotomy between access and no access to the Internet and other technologies; to encompass a range of motivational, skills based, and engagement factors (e.g. Hargittai 2002; Helsper 2012; van Deursen and van Dijk 2010, 2014; van Dijk 2005). However, the challenges of measuring the wider social implications of these diverse digital practices in a quantitative way have remained. Many studies use cross-sectional data where causal influence cannot be assumed, and the social outcome measures used are very weak. Often Internet use is treated as if it is the same as a social outcome. For example, shopping online does not necessarily save money or looking up health information make an individual more healthy yet they are often treated as equivalent (Helsper et al. 2015; Allen 2010). Thus, while many academics support the theoretical assumption that there is a bi-directional and complex relationship between digital and social inequalities the quantitative data available to support such claims is weak. It is important that quantitative research exploring digital and social inequalities develops in order to complement the rich qualitative work in this area to help to dispel these simplistic and deterministic claims.

A small, but growing body of work aims to address this issue, by designing and incorporating items in digital inclusion surveys that ask respondents about the outcomes they have achieved through Internet use. This important work has shown significant differences in how different groups benefit differently from Internet use (van Deursen and Helsper 2015; Van Ingen and Wright 2016; Stern et al. 2009). However, there still remain challenges of participant recall and reliance on cross-sectional data (e.g. DiMaggio and Bonikowski 2008; Van Ingen and Wright 2016; Stern et al. 2009). Thus, additional forms of data are required.

In this article we aim to contribute to research in this area by focusing on Internet use and social class. We explore the value of using longitudinal data and secondary data sets to examine the relationship between Internet use and social class mobility. Using four waves of longitudinal data from Britain we examine the role of Internet (non) use in changes in social class between 1997 and 2013. We quantitatively test whether someone using the Internet at one time-point is associated with change in social class at the subsequent time-point, while controlling for factors known to influence social mobility.

Britain offers a good site for this research. The British government has been active in addressing digital inequalities assuming that their removal will enhance social mobility (DCMS 2017; Helsper and van Deursen 2015; Selwyn 2008). In addition, Britain has experienced significant absolute mobility[1] since the 1950s and 60s (Goldthorpe 2013; Buscha and Sturgis 2015). Further, the government funded British Household Panel Survey (BHPS) and its successor, the UK Household Longitudinal Survey (UKHLS), provide a valuable secondary data set for the analysis.

The Internet and social class mobility

There are a number of ways that the Internet could be shaping social class mobility in both positive and negative ways. Social class and social mobility can be defined in a number of ways. (e.g. Bottero 2005; Crompton 2008; Fortunati and Taipale 2017; Urry 2012). In this article, our focus on social mobility is concentrated on the extent to which individuals move (or do not move) up and down the social class hierarchy. Informed by the work of Goldthorpe (e.g. Goldthorpe 2004, 2007, 2016), we utilise an economic approach to measuring social class that focuses on occupational structures and relations (e.g. Clayton and Macdonald 2013; Williams 2017).

The economic approach to class taken here aligns broadly with a Weberian perspective (Chan and Goldthorpe 2007; Breen 2002), where class is one of three dimensions (the other two being power and status) in social stratification (Weber 1978). This view of social class has been embraced by a number of scholars exploring the relationships between social and digital inequalities (e.g. Ragnedda and Muschert 2015; Ragnedda 2017; Yates et al. 2015; Lindblom and Räsänen 2017; Wessels 2013).

Such an approach to measuring class has been shown as a consistently robust way to understand an individual’s position in society and is strongly related to a wider set of social outcomes for the individual including income and life chances (Connelly et al. 2016). However, it is important to note that there is significant criticism of this approach due to its neglect of more social and cultural dimensions and its earlier focus on the employment conditions of individual men, without proper consideration of women and the family unit (Bottero 2005; Crompton 2008).

While we acknowledge such criticisms, and recognise that there are alternative ways of defining and conceptualising social class, economic definitions of class have a well-recognised (if not always supported) approach in digital inclusion and sociology more broadly. We select this approach because we believe that economics is the central basis for understanding social class relations (Bradley 2014; Clayton and Macdonald 2013), and that at times the strong attention placed in recent years on more social and cultural explanations for social class has risked obscuring the fact that material circumstances continues to have a significant impact on class position and life chances. Furthermore, we suggest this way of conceptualising class aligns with theories that focus on occupations in the information society (e.g. Bell 1973; Reich 1991). Methodologically, quantitatively measuring social class in ways that also incorporated social and cultural dimensions are highly complex and would make the analysis far more challenging, given the presently available data. This latter point is something we will return to in the discussion.

Broadly, there may be a number of ways that the deployment and use of technology may influence social class mobility. This can be both at a structural level, where technology can be viewed as "a structuring network for generating production and participation as an infrastructure in global capitalism" (Wessels 2013, 26) and at the individual level as one (among many) resources "for individuals that enable them to compete to enter the labour market; to engage in politics, culture and education and to participate in social life" (Wessels 2013, 26).

At the structural level, there have been changes in the proportion of jobs classified as knowledge or information work (Bell 1973; Reich 1991). An increase in kinds of informational jobs that improve employment conditions would open opportunities for people to move up the class structure (Goldthorpe 2016). However, outsourcing and technology replacing or de-skilling parts of the workforce may contribute to more downward mobility (Castells 1996; Robins and Webster 1999; Tufekci 2012). Thus, the extent to which technology leads to more positive or negative effects on social class mobility remains an open question.

A similarly mixed picture is apparent at the individual level. On the positive side, Internet use is potentially changing the way people find out about jobs and as a result they could improve their employment prospects (Autor, 2001). Beyond access, it could be that those with digital skills are more likely to get informational jobs that have good employment conditions; improving upward class mobility. Further, Internet use during work could lead to acquisition of skills and knowledge and increase in social, cultural, and economic capital (DiMaggio and Bonikowski 2008). On the other hand, Internet use may not in reality offer any change in circumstances. Those with more social, cultural, and economic resources may instead be able to use the Internet to maintain and reinforce their social class position (Tufekci 2012) and inequalities in the employment structure may remain (Eubanks 2011). Thus again, the role of the Internet in social class mobility is an open question.

To fully explore the range of ways that the Internet may influence social class mobility, we would require a complex data set that would allow us to explore an array of factors at both the individual and structural level. However, current longitudinal data sets do not allow such an approach. Therefore we aim to make a contribution by examining a relatively simple model: specifically the impact of Internet use and non-use on social class over time. Internet (non) use is a necessary prerequisite to all of the possible uses of the Internet to change social class; and it is important for research to continue to pay attention to those individuals who classify themselves as non-users of the Internet (Reisdorf and Groselj 2017; Helsper and Reisdorf 2017; Robinson et al. 2015). Thus, despite its limitations it is a useful contribution to examine what such an approach offers the field.

Methodology

The data used in this paper is from the British Household Panel Survey (BHPS) and its successor, the UK Household Longitudinal Survey (UKHLS). It is the only longitudinal data set in Britain that contains items that measure the two central variables for our analysis, i.e. Internet use and social class. The data set contains an item on Internet use (i.e. whether someone uses the Internet or not), alongside measures of age, gender, health status, and level of education. In line with our conception of social class, we measure it with National Statistics Socio-economic Classification (NS-SeC) data.

To track the impact of Internet use over time, we selected four waves of data to reflect early stage adoption of the Internet up to recent times in ways to have: (1) approximate equivalent time lags between the sweeps, and (2) sufficient time span within which changes in social class (i.e., NS-SeC status) could be observed. Specifically, we selected wave 7 (1997/98), wave 12 (2002/03,) and wave 17 (2007/08) of the BHPS, and wave 4 (2012/13) of the UKHLS. We then removed all full-time students and retirees (for whom no NS-SeC classification exists), and were left with a sample of 2,155 individuals who replied throughout all four waves.

In a longitudinal study such as this it is important to correct for design bias due to unequal selection probabilities and non-response bias due to attrition between the waves (Sadig 2014). Based on the trade-off between accounting for all biases and avoiding reductions in sample size by including cases with weights set to 0 (i.e., "listwise deletion," whereby cases are eliminated from analysis), we decided to only adjust for non-response while keeping all 2,155 cases. We created these longitudinal non-response weights as the inverse of the predicted probability for response/non-response in all four relevant waves based on a logistic regression with age, gender, education, long-term health condition, NS-SeC, and Internet use.

To ensure this was the most appropriate approach, we compared this strategy with three alternative weighting schemes (see Table 1). Yet each alternative approach resulted in the loss of more participants. The first two weighting schemes combined the self-created non-response weights with the design weights of wave 1 and wave 7 respectively, which are supplied as part of the cross-sectional weights in the BHPS/UKHLS. The first resulted in losing 438 cases (those added to the panel between wave 1 and wave 7 as the first relevant wave). While the second only led to a loss of 29 cases, it created methodological complexity, as wave 7 cross-sectional weights include other adjustments beyond the design weights. The third alternative weighting strategy consisted of the longitudinal weights originally provided by the BHPS/UKLHS, which also correct both for unequal selection probabilities and non-response. However, they are set to 0 for everyone who skipped any one of the other 18 BHPS/UKHLS waves that we did not use in our analysis, which resulted in 785 out of 2,155 cases being discarded.

Here we only report the findings using the main non-response weights described above. However, we have run the model using the other three options. While our model coefficients change slightly in each case, the main findings and directions of coefficients are not altered. Further details of alternative weighting and the models produced are available from the authors.

{TABLE 1 ABOUT HERE}

Measures

The measure of social class employed in this study is based on the work of Goldthorpe and colleagues (e.g. Goldthorpe 2004, 2007, 2016) who differentiate class groupings through a combination of differences between employment status (employers, self-employed workers, and employees), and the relationships people have with their employers (employment regulation). Employers alter the kinds of contracts they hold with their employees depending on: (1) the ease with which the quantity and quality of work can be measured; and (2) the uniqueness of the skills, expertise, and knowledge an employee holds (and thus the value lost to the organisation if that individual moves elsewhere). For jobs that are relatively easy to monitor in terms of quantity and quality and the skills required are of a general kind and in high supply, people in this group (typically doing more manual and routine work) will experience hourly pay rates and low levels of job security. This will be very different to the experience and employment conditions of individuals in service or professional jobs carrying out specific and highly skilled tasks where it is far more difficult for employers to track quantity and quality and the risks to the company are greater if they leave to work for a competitor. These employees will experience more pay, a clear career path, educational opportunities, and more security. Workers who are in some form of mixed contract consisting of elements of either the labour contract or service relationship described above will experience differing forms of contract related to pay, security, and flexibility (see for detailed explanation Goldthorpe 2007, 2016).

People with similar employment status and relationships will be in the same class (Chan and Goldthorpe 2007). These class categories are not intended to be meaningful to those who fall within them. While individuals would not necessarily locate themselves in one of the classes, those in the same class are likely to experience similar economic life chances in terms of job stability, security, and opportunities (Goldthorpe 2004; Goldthorpe and McKnight 2006). Furthermore, these class positions have been shown to be good predictors of a wide set of life chances in Britain (Connelly et al. 2016; Goldthorpe 2007).

The NS-SeC's 8 qualitatively distinct categories are based on the conceptualisation of social class advanced by Goldthorpe and colleagues (e.g. Goldthorpe 2004, 2007, 2016). Accordingly, calculating NS-SeC categories is based upon a series of survey questions on people's employment relations and conditions (see Rose and Pevalin 2003; ONS 2017). Despite concerns about increasing wage inequalities, recent analysis of British data shows that NS-SeC remains a very reliable measure of social structure, as inequalities in earnings follow class lines (Williams 2017).

Given the relational and categorical nature of NS-SeC, care must be taken when creating a hierarchical measure of social class. Based on the guidance provided by UK's Office for National Statistics (ONS) we created a four-class hierarchy of social class based on NS-SeC classifications (1= higher managerial, administrative, and professional occupations, 2 = intermediate occupations, 3= routine and manual occupations, and 4 = never worked and long term unemployed) at each of the four sweeps. For example, as discussed above, people in class 1 will experience job security and job advancement and increases in pay whereas people in class 3 are likely to paid on an hourly or weekly basis with far less job security or advancement. We then reverse-coded the scale so higher values indicate higher social class. This scheme enables us to create the hierarchical measure for our analysis. However, it does mean that classes of people with mixed forms of service relationships and labour contracts are grouped together (under intermediate occupations). The implications for our results are discussed below.

We used repeated measures of Internet use (0 = non-user, 1 = user) and we controlled for age in 1997/98 (M = 34.2, SD = 8.9, Range = 15-80) and gender (0 = male, 1 = female) both as time invariant covariates. Educational level as measured by the response to “highest academic qualification” was coded as (1 = low, 2 = mid, 3 = high; where "Higher Degree", "1st Degree" and "HND, HNC" was categorised as high; “A Level", "O Level," and "CSE”[2] was categorised as mid; and the remainder as low). There were 3810 people who could not be classified by this system (from the first wave), so for these people we used the International Standard Classification of Education (ISCED). "Primary" and "low secondary" were categorised as low; "lower secondary-vocational" and "hisec-mivoc" [3] were categorised as mid; and "higher vocational", "first degree," and "higher degree" were categorised as high. To distinguish between those with and without a long-term health condition, health status (0 = no health problem, 1 = health problem) of individuals was included as time-varying covariates at each point in time.

Age, gender, health, and education are well-established factors for social and digital inequalities (van Dijk 2012; Bottero 2005). For example, education is often viewed as a way to support social mobility (Wessels 2013), yet many studies show that those with means tend to be better able to secure and benefit from education (Bukodi and Goldthorpe 2011; Goldthorpe 2013; Platt 2011). Similarly, research has shown that those with poorer health are more likely to experience downward mobility (Lundberg 1991). Likewise, education, age and health problems are consistently shown to be a source of digital inequalities in the British context and elsewhere (Ofcom, 2016). Therefore these factors are included in the model.

It is important to note that the first three waves of the data set did not include any variables that measure types of Internet use, quality of Internet access, and digital skills. The fourth wave had a few questions about the nature of Internet use but remained highly limited. Measures of digital skills were also lacking. This is a limitation of the data set and thus of the model, which is discussed later in the discussion on implications for future research.

Analytic procedures

After presenting descriptive data, we specified a reciprocal effect model, in which we estimated both autoregressive and cross-lagged paths between prior and subsequent social class, and Internet use respectively (see Figure 1). In the autoregressive part of the model we estimated the effect of a variable at a prior time-point predicts the same variable at a later time-point, alternatively expressed, e.g., social class at time T regressed on social class at time T-1. A significant autoregressive effect means that the participants maintained a relative rank-order from time T-1 to time T (i.e., rank-order stability). In the cross-lagged part of the model we estimated paths from social class at time T-1 to Internet use at time T, controlling for Internet use at time T-1, as well as paths from Internet use at T-1 on social class at T. A significant effect of the prior-social-class-on-later-Internet-cross-lag indicates that a higher prior social class at T-1 predicts an increase in Internet use at T. In contrast, the prior-Internet-use-on-later-social-class-cross-lag indicates that more Internet use at T-1 predicts an increase in social class at T.

At the first time-point social class and Internet use were associated, and at later time-points the disturbance terms were associated. As the indicators were ordinal we used the Weighted Least Square Mean Variance (WLSMV) estimator in Mplus (Muthèn and Muthèn 2012). The observed thresholds of the ordinal metric represented an underlying continuous continuum. Using the theta-parameterization in Mplus we allowed residuals to be estimated on this basis. A negligible 1.82% missing data-points missing of the dependent variable were estimated using the default full information maximum likelihood (FIML) in Mplus (Muthèn and Muthèn 2012). The final model included time-invariant and time-varying covariates. We applied sampling weights as discussed above. We estimated good model fit for autoregressive models using continuous outcomes using a Root Mean Square Error of Approximation (RMSEA) of $\leq .05$, a Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) $\geq .95$ (e.g., Browne and Cudeck 1993), and the Weighted Root Mean Square Residual (WRMR).

Results

As a first step in the analysis we examined the proportion of individuals who moved up, down, or stayed in the same class category as measured by NS-SeC in 2012/13 compared to 1997/98 against when they became Internet users (or never used the Internet). The results are summarised in Table 2. Overall intra-generational mobility is most stable in NS-SeC 4 (the highest class) where over 70% remain in the same class over this time period, with upward mobility being quite common in the other three classes. This is particularly the case in NS-SeC 1 (the lowest class) where only 28% remain in the same class. However, the fact this group cannot move any further down the class scale should be noted. This upward mobility could be reflecting changes in job structure over the 15 year time span where more professional and managerial jobs particularly in information and technology sectors (i.e., jobs in NS-SeC 4) became available and therefore there were more possibilities for people to move up (or remain at the top). It is important to note that these structural changes may not mean a lot in real terms for the individual – if everyone is moving up then everyone essentially stays the same, relatively.

People who have never used the Internet are more likely to stay where they are or end up in a lower NS-SeC group between 1997/98 and 2012/13 compared to others in the same NS-SeC group who used the Internet. The earlier members of NS-SeC 3 and NS-SeC 2 used the Internet the more likely they are to move up to a higher NS-SeC category; and similarly members of NS-SeC 4 were more likely to maintain their status. The implications for NS-SeC 1 seems less clear-cut, although the pattern is relatively similar with early Internet take up being related to movement upwards. These patterns suggest that Internet use has a positive impact on social class mobility, and also support prior research findings that experience with the Internet is an important factor for Internet engagement (Venkatesh 2003) and those who have spent more time online are more likely to use the Internet for a wider range of purposes and benefit more from this engagement (Eastin and LaRose 2000; DiMaggio and Bonikowski 2008).

{TABLE 2 ABOUT HERE}

Our findings suggest that the Internet could influence social class membership and play a role in social class mobility. However, while these descriptive statistics are informative, they do not offer a sophisticated analysis of how Internet (non) use relates to social class over time, controlling for education, age, gender, and health.

Therefore we ran the model as described in the analytic procedures section. We observed autoregressive and cross-lagged relationships in the reciprocal effects model. A first model, in which the auto-regressive paths, associated within time-point variables or residuals, and cross-lags were specified, fitted data well ($\chi 2$ [12]=24.20; p = 0.019; RMSEA = 0.022; CFI = 0.999; TLI = 0.998; WRMR = 0.518). All variable thresholds were allowed to vary across the time-points. In the next model we included all covariates, which also fitted data well ($\chi 2$ [60]=134.285; $p < 0.001$; RMSEA = 0.024; CFI = 0.992; TLI = 0.985; WRMR = 0.987).

{FIGURE 1 ABOUT HERE}

Figure 1. Reciprocal effects between social class (NS-SeC) and Internet use (IU) between 1997 and 2013

Note. Data was weighted using the main non-response weights described in the methods section. Gender, age and educational level were included as covariates. Weighted Least Square

Mean Variance estimates are standardized coefficients from Mplus 7.4 (Muthén & Muthén, 2014)

As shown in Figure 1, social class was stable from one time-point to the following (βs = .66, .61 and .80) and indeed appears to become stronger over time. In other words, previous social class has a highly significant effect on current social class. A similar trend was found for Internet use, where being an Internet user or not was stable over the time points (βs = .67, .59 and .67). In other words, once people begin to use the Internet, most (although not all) are likely to continue to use it.

Consistent with other research, the model demonstrates the relationship between social and digital inequalities; social class was positively associated with Internet use in 1997/98 (ρ = .29). More uniquely, the model shows the relationship between social class and Internet use over time. Internet use in 2002/03 predicted a higher social class in 2007/08 (β= .13), and Internet use in 2007/08 a higher social class in 2012/13 (β= .10). These effects were of the same magnitude as the effects of social class on subsequent Internet use (β= .13 and .21). Thus, Internet use predicted social class in 2007/08 and 2012/13 controlling for previous social class and also controlling for age, gender, health, and education.

{TABLE 3 AND 4 ABOUT HERE}

From examination of the covariate effects in the model in Tables 3 and 4, it can be seen that all four covariates, age, gender, health, and education have an impact on social class. Most notably, inequalities in health persist; as having a health condition has a negative effect on social class at all four time points.

As can be seen in Table 4, beyond class, the other main predictor of Internet use is age in 2007/08 and 2012/13, with those who are younger being more likely to use the Internet at each time point. The importance of age in uptake on Internet use is well supported in a wide range of literature (Yates et al. 2015; Ofcom 2016).

Discussion

Our study provides some empirical evidence that in Britain Internet use has a positive effect on social class mobility, controlling for age, gender, education, health, and previous social class membership. In addition, it finds a relationship between social and digital inequalities; where social class was positively associated with Internet use in 1997/98; and social class in 2002/03 predicted Internet use in 2007/08, with a similar relationship between 2007/08 and 2012/13. We acknowledge that because of the limitations of the study design our results still do not imply causality. Causality requires not only temporal precedence and a plausible mechanism, which have been shown here, but also that the association always holds (which requires another dataset).

As Figure 1 shows, Internet use in 1997/98 did not predict social class in 2002/03. This is perhaps to be expected, given that Britain had only recently begun to deliberately invest in the information and technology sectors, the dot com boom and collapse occurred within this period, and Internet penetration rates in Britain at that time were low (OxIS 2003); and this may also be why social class in 1997/98 did not predict Internet use in 2002/03. Taken together, it is reasonable to argue that the Internet was not influencing the everyday lives of many people at that time. This pattern changed after this point in time, where Internet use at 2002/03 and 2007/08 predicted social class in 2007/08 and 2012/13 respectively, controlling for previous social class, gender, education, health, and age; and similar patterns were found for the impact of social class on Internet use. This likely reflects the growing role of the Internet in daily life. In summary, being an Internet user has a positive impact on social class over time.

These findings support calls for implementation of policies to ensure that everyone has access and the skills to use the Internet (e.g. Yu 2006; van Dijk 2013), as non-Internet users do appear to miss out. However, this in itself is a complex task (Reisdorf and Groselj 2017). Individual level interventions alone are unlikely to address the challenge of increasing social mobility (Goldthorpe 2013), and the provision of access and support for digital skills development is not some kind of panacea for issues related to social inequality (Lenert et al. 2012; Wessels 2013).

While the model developed here provides useful substantive insights, it also offers a useful case to examine the methodological challenges with such an approach and discuss a future research agenda.

Future longitudinal research of this kind needs to incorporate a wider set of measures beyond those available in the BHPS / UKHLS dataset to better understand how motivations, digital skills, and engagement relate to social class and other facets of social stratification. This call for more nuanced variables in large-scale longitudinal data sets such as the BHPS and UKHLS is motivated not only by a want to develop more sophisticated empirical models, but also to make far better connections between such data analysis and the extensive theoretical work on digital inequalities, social class, and social mobility. Currently, there is a significant gap between theory and available data which needs to be addressed.

In this article we have used an economic measure of class that aligns with a broadly Weberian perspective (Chan and Goldthorpe 2007; Breen 2002). However, in the current model we have only measured class. In future work it would be important to explore how the Internet shapes power and status as well as class to fully explore the role of the Internet in Weber's theory of social inequality (e.g. Ragnedda 2017; Lindblom and Räsänen 2017). Future research could also conceptualize class through a social and cultural lens (Bakardjieva 2011) – although cultural explanations of social class are particularly difficult to empirically operationalize in survey work (Bradley 2014). Relatedly, there may well be possibilities to use such data sets to explore alternative ways to conceptualize social mobility beyond the focus on social class measures used here (Fortunati and Taipale 2017).

In this article, we have focused on aspects of intra-generational absolute mobility. As noted earlier, investment in knowledge and information sectors by government may well lead to changes in absolute mobility over time (Goldthorpe 2013); and this has been supported by the research here. However, these changes in absolute mobility do not imply changes in relative social mobility. Therefore, another important area for future research would be relative changes in social mobility – which is central for understanding the level of social inequality in a society (Payne 2012). Technological deterministic policies tend to be based on the assumption that technological investment leads to positive effects on absolute and relative mobility (Goodwin and Spittle 2002; Melin 2009). Yet, from the few quantitative studies available, this is not necessarily the case with regard to relative mobility. Studies in Finland have shown that investment in information society projects and the increase of informational and knowledge workers have not led to a more equal and fairer society (Blom et al. 2002; Melin 2009; Pyöriä 2007). In fact, Blom et al. (2002) note, drawing on Castells (c.f. Castells 1996), the risk of polarising the workforce into informational workers who are valued and considered "core" and those who are in effect disposable is very real.

Since social class membership tends only to stabilise when people are in their mid to late 30s and the Internet is a relatively new phenomenon, examining the influence of the Internet on relative mobility is problematic with the current data set. The conclusions we could draw from such an analysis would be tentative at best. However, in a few years' time questions of relative mobility could be sensibly explored. Taking relative mobility as an analytical focus and using the statistical approaches outlined by Breen (2004), we could examine mobility between all eight classes of the NS-SeC scale. This would be particularly valuable for unpacking the processes in our current NS-SeC 2 group, wherein employment relations comprise of a mix of service and labour contracts and also include the self-employed. With the rise of self-employment (Williams 2017) and the "hollowing out" of occupations in this category due to outsourcing or advances in technology (Autor et al. 2003; Goos and Manning 2007; Michaels et al. 2014) this group requires in-depth attention in future work. Interestingly, in our data set the proportion of people who were self-employed did not increase significantly over the time period (from around 5 to 7 %) but this pattern may have changed since 2014.

In summary, there is a range of ways in which longitudinal data may help shed light on aspects of social and digital inequalities that are difficult to quantitatively test in other ways. Such work would help inform decisions on how to use technology to support social inclusion. As Warschauer suggests “the starting point for a progressive consideration of ICT in any institution should not be the digital divide and how to overcome it but rather the broader social structures and functions of the institutions and how ICT might be used to help make them more democratic, equitable and socially inclusive” (Warschauer 2004, 209). Yet, the evidence required for examining questions of relative mobility to support such policy changes can only be achieved through the use of longitudinal data sets that have more sophisticated measures of digital social life as discussed here.

Conclusion

Many have argued that the Internet plays a role in maintaining, exacerbating or changing social inequalities in various ways (van Dijk 2005; Silverstone and Hirsh 1994; Selwyn 2004; Wessles 2013). Our article contributes to this debate by providing a relatively unique analysis of longitudinal data on Internet use and social class membership in Britain.

We are not claiming here (nor does the data show) that Internet use can be considered the primary factor in explaining social class mobility. Class origins are far stronger in predicting a person's future social class over the 12-year period of our study. We also acknowledge the possibility that while we have controlled for the most likely contenders, there may be another factor not used in this model that may explain the relationship we have found. It could be, for example, that Internet use could reflect an agentic orientation to everyday life, which is more about trying new things, rather than use of the Internet per se. We also acknowledge it is important to be mindful of research that has shown that moving upwards in the class structure does not necessarily lead to increase in life satisfaction (Sorokin 1959).

Nevertheless, the analysis provides evidence that in Britain Internet use has an effect on social class mobility, controlling for age, gender, education, health, and previous social class membership. The model we have provided does not provide evidence of the extent to which the Internet is making things more or less equal in society overall, but it does, despite its limitations, suggest that Internet use is now important for maintaining or improving class position. Individuals who used Internet were more likely to end up in a higher NS-SeC group between 1997/98 and 2012/13, even when we control for other factors like education, health, age, and gender. However, it may be that everyone is moving up and therefore it does not make any real qualitative difference if you use the Internet but it would make a significant difference if one did not use the Internet, as such individuals are likely to remain in the same class grouping or move down. Thus concerns about digital inequalities remain highly relevant.

We recognise that the quantitative model we have built cannot account for how people experience these changes in social class or being an Internet user, and is unable to reflect the complex and varied experiences of individuals living within each of these broad class categories (Bottero 2005). Instead, we see this study as contributing to the beginnings of more complex uses of longitudinal data by Internet researchers, which would allow us to quantitatively test theories of technology and social change where individual action and social structure shape each other over time. This additional lens in digital inequalities research, alongside other approaches and techniques, can encourage more debate about the kind of society we want to create and how technology can (or cannot) help to support these changes.

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Table 1. Weighting options.

	Main non-response weights	Non-response weights with cross-sectional weights from Wave 1	Non-response weights with cross-sectional weights from Wave 7	Original weights provided by the BHPS/UKHLS
Adjusting for non-response bias	Yes	Yes	Yes	Yes
Adjusting for design bias	No	Yes	Yes	Yes
Source	Self-created	Self-created	Self-created	BHPS/UKHLS
Resulting sample size	2,155	1,677	2,126	1,370

Table 2. Mobility trends.

	NS-SeC 4 mobility from 1997/98 to 2012/13			*NS-SeC 3 mobility from 1997/98 to 2012/13*			*NS-SeC 2 mobility from 1997/98 to 2012/13*			*NS-SeC 1 mobility from 1997/98 to 2012/13*		
	Up	*same*	*down*	*up*	*same*	*down*	*up*	*same*	*Down*	*up*	*same*	*Down*
Users since 1997/98	-	89.1	10.9	41.2	41.2	17.6	60.0	40.0	0.0	71.4	28.6	-
Users since 2002/03	-	74.2	25.8	38.4	46.7	14.9	49.5	48.6	1.9	87.2	12.8	-
Users since 2007/08	-	73.2	26.8	19.8	59.4	20.8	42.6	56.8	0.6	86.5	13.5	-
Users since 2012/13	-	62.0	38.0	17.2	62.1	20.7	21.8	71.4	6.7	54.2	45.8	-
Non-users	-	44.4	55.6	9.5	66.7	23.8	17.1	72.9	10.0	37.8	62.2	-
Overall	**-**	**74.7**	**25.3**	**30.2**	**52.3**	**17.5**	**38.2**	**58.4**	**3.4**	**71.2**	**28.8**	**-**

Note: NS-SeC has been reverse coded. NS-SeC4 is the highest class, and NS-SeC 1 the lowest.

Table 3. NS-SeC covariates.

	NS-SeC 1997/98				*NS-SeC 2002/03*				*NS-SeC 2007/8*				*NS-SeC 2012/13*			
	B	*SE*	*p*	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*	β
Age	.023	.004	<.001	.190	.003	.005	.511	.019	.003	.005	.492	.016	-.012	.007	.084	-.043
Education	.483	.206	.019	.266	.468	.400	.242	.190	.808	.400	.043	.279	.353	.325	.277	.086
Gender	-.186	.072	.010	-.086	-.133	.085	.117	-.045	-.086	.085	.311	-.024	.346	.116	.003	.071
Health	-.749	.135	<.001	-.199	-.470	.160	.003	-.093	-1.04	.161	<.001	-.187	-.729	.184	<.001	-.122

Table 4. Internet use covariates.

	Internet use 1997/98				*Internet use 2002/03*				*Internet use 2007/8*				*Internet use 2012/13*			
	B	*SE*	*p*	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*	β
Age	.009	.008	.251	.082	-.013	.008	.119	-.084	-.018	.006	.002	-.116	-.045	.011	<.001	-.171
Education	.323	.247	.192	.187	-.601	.497	.227	-.260	.626	.506	.216	.274	.974	.661	.140	.241
Gender	-.284	.131	.031	-.137	.059	.157	.708	.021	.043	.110	.696	.016	.293	.233	.209	.061
Health	-.280	-1.43	.153	-.078	.015	.216	.945	.003	-.157	.198	.426	-.036	.181	.295	.541	.031

Notes

[1] Absolute rates of mobility refer to the actual proportions of individuals of given class origins who are mobile to different class destinations, while relative rates compare the chances of individuals of differing class origins arriving at different class destinations and thus indicate the extent of social fluidity (Goldthorpe 2013). In a society with high fluidity where people start out from has less effect on where they end up.

[2] HNC and HND stand for the Higher National Certificate and Higher National Diplomas respectively. They are British qualifications that are broadly equivalent to one year or more of University Education. ‘A-levels’, ‘O-levels’ and ‘CSEs’ are all various forms of subject specific qualifications that are taken by school children in England and Wales at the age of 16, 17 and 18.

[3] “hisec-mivoc" is used in the BHPS data set to denote qualifications that fall within the mid vocational range.